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Highlights

Optimizing operational costs and PV production at utility scale: An optical fiber network analogy for solar park clustering

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- Modeling analogy with optical network design for optimal PV site clustering
- Enhanced risk management of operational costs and energy stability
- Comparative study with an existing GIS-optimization model on real data
- Novel implementation strategy for PV site selection at utility scale

Optimizing operational costs and PV production at utility scale: An optical fiber network analogy for solar park clustering

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Abstract

Increasing the share of renewable energy sources in power systems is key to a successful energy transition. Optimal renewable site selection requires a holistic approach, involving land, resources, environmental and economical data and constraints. In this paper we consider the problem of solar PV penetration into the power network as a spatiotemporal analysis combined with decision support targeted for policy makers and investors. Our goal is to seek new models that maximize energy penetration and stability into the network, while minimizing the operational costs. We show how the selection of solar PV sites can be accomplished to satisfy such objectives by investigating the optimal clustering of multiple solar PV parks around a shared electrical substation. This is a combinatorial problem in terms of all the potential clusters given the set of PV site candidates. Our main contribution lies in identifying and proposing a modeling analogy of our problem with the so-called SONET problem, tackled in fiber network designs. We show how this new spatiotemporal PV park placement model minimizes operational costs, while increasing energy stability of the solutions produced. We also introduce a GIS preprocessing step to reduce the computational cost of the proposed approach. We compare our proposed SONET-based model to an existing GIS-optimization model on a real case study and data from the French Guiana's power system. This new approach aggregates multiple PV parks into clusters distributed across the territory. In the case of French Guiana, the same global nominal power (≈ 45 MW) can, for instance, be distributed among 11 PV parks and 3 clusters, against 3 large-scale PV parks. Results show substantial gain in costs per kWh produced, up to 10 MW of extra installed power and 16 GWh of extra power generation when considering PV parks ≤ 5 MW. The new cluster configuration also ensures improved energy stability of the solutions, resulting in mitigation of the risks for both the network manager and the decision maker.

Keywords: Energy planning; Spatial decision support; Spatiotemporal data; Solar PV; SONET

Nomenclature

a_{ref}	Product of diode ideality factor, number of cells in series and thermal voltage at reference conditions (V)
Adjust	Adjustment to the temperature coefficient for short circuit current (%)
B_k	Boundary set of nearest PV sites corresponding to ring R_k
C	Substation maximum hosting capacity (kW)
c_{ik}	Nominal capacity of site PS_i in ring R_k (kW)
$Ccap_k$	Capital cost for implementation of new PV plants in ring R_k (€)
$Ccon_k$	Connection cost for each ring R_k , transmission lines (€)
$Clan$	Transmission line unit cost (€/m)
Cop_k	Annual operational cost for PV plants in ring R_k (€)
$Csta_k$	Capital cost for new substation per ring (€)

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D	Distance threshold (m)
d_{ij}	Distance between site PS_i and site PS_j (m)
Dem_h	Estimated hourly power demand (kWh)
Dg_i	Shortest distance from the grid to the centroid of a candidate PV site (m)
$Eint_h$	Current hourly production from intermittent sources (kWh)
Ep_h	Current hourly production from non-intermittent sources (kWh)
h	Hour of the year
I	PV cell output current (A)
i	Site index
I_0	Diode reverse saturation current (A)
I_L	Photocurrent (A)
$I_{0,ref}$	Diode reverse saturation current at reference conditions (A)
$I_{L,ref}$	Photocurrent at reference conditions (A)
k	Ring index
M	Big number
n	Number of candidate PV sites derived from GREECE
nN_sV_{th}	Product of diode ideality factor, number of cells in series and thermal voltage (V)
$Pnom$	Nominal power per unit area (kW/m ²)
$Ppv_{h,i}$	Estimated hourly power production per PV unit for each site (kWh/m ²)
PS	Set of potential sites
R	Set of potential rings
R_s	Series resistance (Ω)
$R_{sh,ref}$	Shunt resistance at reference conditions (Ω)
R_{sh}	Shunt resistance (Ω)
SA_{ik}	Surface area of new selected PV park belonging to ring R_k (m ²)
$Smax_i$	Maximum area for each site (m ²)
$Smin$	Minimum site area (m ²)
V	PV cell output voltage (V)
x_{ik}, y_k	Boolean decision variables

1. Introduction and related work

Nowadays, the main goal of most countries' energy planning policy [1] in terms of *energy transition*, relies on the integration of renewable-based generation in power networks. This enjoys many advantages among which, contributing to sustainable energy access, mitigating climate change, and tackling several of the sustainable development goals (SDGs) [2]. However, increasing the share of renewable energy (RE) sources in power networks remains a challenge, due to their inherent intermittency and geographical dispersion [1]. Specific planning strategies based on spatiotemporal data and decision support models [3] must be developed accordingly, in order to reach *energy transition* targets without threatening the existing infrastructures.

1.1. RE planning and spatiotemporal modeling: a literature review

Existing RE planning approaches typically rely on spatiotemporal modeling tools involving different scales and with different objectives and purposes [3]. Various decision support models have been proposed for the integration of RE technologies into energy supply infrastructures. Available works range from local (urban, district) to global scale (country, continent) and involve both temporal and spatial dimensions, mainly through the use of geographic information system (GIS), multi-criteria decision making (MCDM), optimization or bottom-up models. We summarize below the latest and relevant studies in the field, from local to global scale.

Studies at local scale depend on both the specific geometric constraints (rooftop area) and local scenarios of the problem. Various works have combined geographic information systems (GIS) with time series analysis in order to find optimal location and size of RE power sources in urban environments. For instance, Mavromatidis et al. [4] have developed a framework to plan the integration of solar PV and storage in a village, in order to meet the local electricity demand. The authors build solar radiation hourly profiles for each building, and aggregate synthetic electricity demand profiles in order to retrieve the total hourly demand of the village. Finally, they use a mixed-integer linear program (MILP) to select the best rooftops for solar PV installation so that total costs are minimized and RE share is maximized. At municipal scale, Lindberg et al. [5] combine GIS and power flow analysis for solar PV site selection. They analyze both land use suitability and grid hosting capacity when implementing solar PV parks at utility scale, according to specified scenarios of nominal capacities. It eventually results in *approved* PV sites, that is sites for which a PV park might be built (land suitability) without requiring grid reinforcement (hosting capacity). Similarly, Ramirez-Camargo and Stoeglehner [3] have developed a spatio-temporal GIS model for selection of the best RE sites. First, potential sites (size, location) are retrieved from a set of rooftop areas that have been classified according to solar PV usage. Finally, a decision tree is used to find the optimal match between RE generation and electricity demand of the municipality. Regarding pure spatial assessment at urban scale, with no temporal dimension, Thebault et al. [6] have developed a multicriteria sorting tool in order to assess the suitability of a roof to host solar PV systems. The authors combine GIS with the ELECTRE TRI methodology according to predefined weighted criteria such as superstructure constraints, economic feasibility or yearly solar irradiation in order to sort roofs of a given area with respect to its degree of suitability. They apply their method to a district of Geneva, Switzerland and produce a map of the degree of suitability of each rooftop in the given area, from low to very high. Mrówczyńska et al. [7] also use GIS and multi-criteria analysis in order to identify the main criteria for proper RE policy in urban environments. Through fuzzy assessment of expert-based criteria, the authors build an Energy Potential Index (EPI) informing on the feasibility of implementing RE-based individual energy scenarios in various districts of the city of Zielona Góra, Poland. The use of fuzzy-logic also allows to identify the impact of each criterion on given RE policy scenarios, and thus to determine the most optimal conditions for RE development. Results eventually highlight the odds for each individual scenario to be successfully implemented, according to the EPI value and the corresponding city quarters. At the scale of the district, Alhamwi et al. [8] have proposed a cellular approach whereby a given area (city, district, etc.) is divided into several interconnected *energy cells* in which energy demand and supply are balanced at hourly scale. Extra power and storage are appended to each energy cell in order to meet local electricity demand at minimal cost. It results in every energy cell getting optimal storage capacity and power supply configuration. The authors finally use a post-processing GIS-based allocation method for sizing and siting of storage elements in each energy cell.

At the national or regional scale, various studies also focus on providing *suitability maps* through GIS approaches, often combined with MCDM methods, such as analytic hierarchy process (AHP) [9], fuzzy logic [10], etc. Those maps are specifically designed to give information to the decision maker about the best regions for RE deployment in a given territory (country, region). Typically, multi-layer overlay analysis is performed in order to eventually get the available land based on current geographical constraints [11]. Suitability of the available areas is then evaluated according to predefined weighted criteria derived from the literature or from local expertise [12]. GIS-MCDM studies do not aim at taking resource temporal variation or energy demand satisfaction into consideration. Instead, this approach is based on static data and looks for providing spatial information about the RE source potential in a given region. In that line of work, Ruiz et al. [13] have combined GIS and AHP to assess the best suitable area for large scale solar PV plants (> 5MW) in West Kalimantan Province, Indonesia. They first use GIS modeling in order to remove constraint layers, and then consider criteria layers according to 3 main factors (climatology, topography and proximity). The weights of the 9 criteria the authors have selected are obtained through the AHP priority-matrix normalization method. Accordingly, they generate 4 site suitability classes from least suitable to best suitable to evaluate the relevance of the potential areas in terms of solar PV power. Regarding dispatchable resources (no time involved) such as biomass, Jayarathna et al. [14] have applied GIS and fuzzy multi-criteria analysis in order to find the optimal sites (location, size) for bio-energy power plants in Queensland, Australia. GIS allows the exclusion of unsuitable locations,

then fuzzy logic is applied to standardize the chosen criteria, and finally AHP is used to assign weights to those criteria. Once potential sites are known, spatial biomass availability is assessed and implemented into a location-allocation optimization analysis along the road network and the delivery costs. Optimal location and size of the corresponding power plants are finally retrieved, according to two specific scenarios (centralized vs. decentralized and small-scale vs. large-scale). At higher scale, Yang et al. [11] have recently proposed an innovative GIS-based approach in order to assess large-scale PV power generation over China. The authors first exclude protected areas and unsuitable land cover, and then classify the resulting suitable PV areas into different categories according to solar radiation levels. Large-scale PV generation is then derived from land conversion factors corresponding to given technical and geographical conditions. Associated life-cycle CO₂ reduction from the use of large-scale PV is also computed. The final result is a map of the large-scale PV generation capacity potential with related CO₂ emission reduction potential for each province in China.

Another line of work and objectives is the search for optimal energy system configurations through the use of bottom-up models. Typically, this holistic approach allows for an in-depth analysis of the potential contribution of RE sources in power systems [15]. Though bottom-up models are especially useful for guiding RE policy road maps at broader scale and longer time horizon [1], they are not designed to identify the geographical distribution of the corresponding RE sources. Instead, those models aim at assessing the optimal RE share in the whole system or in the sub-systems, with respect to given objectives (e.g. maximizing RE generation and minimizing total costs) [16]. Zhao and You [17] have used this approach to determine the potential RE transition pathways for the electricity sector in New York State. They developed a robust linear optimization framework, in which the objective function is to minimize the total electricity transition cost under specific constraints such as electricity demand, market availability of wind turbines and solar PV, targets on RE generation and greenhouse gas emissions, etc. It results in specific electricity generation shares for the different power sources, including RE technologies, in the given time period (2020-2035). Similarly, Bogdanov et al. [18] have applied the LUT Energy Transition Model in order to evaluate options and barriers on the pathway towards a full RE-based system in Kazakhstan by 2050. This model is based on hourly time step simulation and linear optimization; it aims at minimizing the total integrated energy system cost while satisfying hourly profiles of power demand, water heating demand as well as energy demand from transport and industry. Every technology (electricity generation and transmission, energy storage, heat generation, transportation, etc.) is modeled based on its current state of the art and integrated into the whole system structure. According to 5 different transition scenarios, results eventually emphasize the optimal share of each given electricity generation and energy storage technology in the system at each 5-year time step between 2015 and 2050. At broader scale, Zappa et al. [19] have used the bottom-up approach to evaluate the feasibility of a European power system only based on RE sources by 2050. The authors model the continent as a single integrated power system where RE capacity can be shared between countries. Intermittent RE resources are estimated through available profiles from ERA-interim. Finally, 7 scenarios corresponding to a fully RE-based power system are analyzed. Simulation is run at hourly time step and a MILP optimization is performed for minimizing the life-cycle cost of the whole system. Also, Frysztacki et al. [20] have analyzed the effect of network and resource resolution on the PyPSA-Eur model of the European electricity system, when considering high shares of wind and solar energy. The model is run at 3-hourly temporal resolution, and the objective is to minimize investments and operation costs for wind, solar, open cycle gas turbines, batteries, hydrogen storage and transmission. To evaluate the effect of network resolution, the number of nodes of the PyPSA-Eur model is varied from 1024 to 37 country-zones, by using the k-means algorithm. Finally, results show that grid resolution over 90 nodes is required to fully capture costs and technology investments, while better resource resolution discloses more advantageous onshore wind sites.

1.2. The GREECE-OPSPV decision support framework

As we stated in [21], optimal site selection (location, size, total number) satisfying spatial and temporal constraints at utility-scale requires enhanced decision support models. This is mainly due to the specific set of objectives, scenarios and constraints of the approaches we have previously depicted. For instance, the utility scale brings out new scenarios in contrast with the local scale: climate and weather variations throughout the territory, intermittency (no storage), terrain issues (slope, land use, etc.), the size of the study area or the lack of predefined geometric constraints (rooftop areas). On the other hand, GIS-based MCDM approaches return the most suitable RE areas based on static resource assessment and expert-based decision criteria. They do not aim at optimizing the total number, location and size of power plants while satisfying the energy demand (except for dispatchable resources such as biomass which only require spatial optimization). Finally, bottom-up models support techno-economic feasibility of RE system configurations and provide optimal shares of RE capacity per system or sub-system. Their main objective is to guide RE policy road maps at global scale and long time horizon. This holistic approach does not link temporal scenarios with a territory's own geographical constraints and related costs.

Accordingly, we recently proposed an integrated model framework, combining GIS and Robust Optimization (RO), called the GREECE-OPSPV system (*Geographical RENEwable Energy Candidate Extraction - Optimal Planning and Sizing of PV parks*) [21, 22], that fills the gap between pure GIS approaches and bottom-up models, by handling interdependent spatial and temporal constraints for site selection at regional scale. It tackles the optimization problem of identifying the best sites (location and size) that increase solar energy penetration into the power grid at minimal cost, while satisfying the region’s specific constraints (terrain, resource dispersion, infrastructures, etc.), related costs and energy planning targets. More specifically, the GIS component (GREECE) gathers large heterogeneous sets of spatiotemporal data, and allows for location and size of the best solar PV parks to be retrieved with respect to geographical constraints (restricted areas, land use, distance to grid, etc.), spatial dispersion of the resource, hourly global energy demand and generation, predefined planning scenarios, and the degree of risk adversity authorized by the decision maker. Through a set of spatiotemporal data layers and control parameters, the GIS module converts spatial constraints and parcels into *items* characterized by *de-spatialized* attributes and solar resource time series for each candidate PV site. Based on current electricity generation and demand time series as well as projection scenarios, the RO model (OPSPV) then derives optimal sites (location, size and power), with respect to given temporal constraints (parcel size, hourly electricity demand, maximum penetration of intermittent RE power) and objectives (maximize energy generation and minimize total costs). The model finally returns an estimate of the risk associated with solar PV investment at utility scale, for the decision and policy maker, by means of a Pareto approach (cost vs. energy generation) and according to best and worst case scenarios. Each solution is defined by (1) the total number, (2) the geographic location and (3) the nominal power and size of all the utility-scale PV parks that could be installed in the future throughout a given region.

The GREECE-OPSPV decision support model is built on the assumption that for each solar PV park contributing to the solution, a new substation is accounted for, guaranteeing the connection to the power network. This model made sense since it was designed for private investors in RE plants, thus each park required its own independent connection to the grid. This can be a globally costly approach that might not benefit nor be suitable to all network configurations. For instance, in island networks (i.e. not interconnected), the network manager might have the authority to decide which park should be turned on and off, depending on the share of intermittent power [23], rendering some substation underused. Accordingly, some investors have moved on to diversifying their RE investments (hydro, biomass, etc.) or exploiting power plants with added storage capacity to ensure a regular income [24].

1.3. Solar park clustering for optimizing operational costs and PV production

In this paper we investigate an alternative solution, that would rely on a co-investment, whereby several parks belonging to multiple investors would be connected to the same substation. To our knowledge this approach has not been investigated in terms of simulation models, that optimize costs and production. This would lead to a cost-effective solution in such situations when the maximum power per RE park is constrained by the technical features of the power network, leading to many small parks against fewer large parks. In fact, for multiple small-scale solar PV facilities, the existing model leads to a cost curve that grows with the number of corresponding substations. By *small-scale* power stations, we here mean smaller facilities from a utility-scale point of view (utility-scale projects are generally defined for rated output capacity of 4 MW or above [25]). It is important to keep this in mind, as we will maintain this designation throughout the paper. We address this issue and propose a computational and tractable model that mitigates the cost, through the aggregation of various power plants around one unique substation. Both the sets of aggregated plants, and the substation location need to be optimized, leading to a combinatorial search problem. In this article we show how to address this combinatorial problem in a tractable manner, by addressing the challenges it raises on both the existing GIS and optimization models.

The optimization problem we address is to maximize PV energy supply and minimize costs through small-scale power facilities. We show how the small-scale approach can improve network management, reduce risk adversity as well as allow for better solar PV plant modularity in the future. A key contribution is a new framework that exploits an analogy with the Synchronous Optical NETWORK (SONET) [26] to reduce the combinatorial explosion resulting from the aggregation of potential parks during their selection. The SONET is a popular network design in the field of fiber-optic technology. Our contributions are the following: 1) to tailor the constraints of the SONET optimization problem to our own and integrate them into the RO model of the framework, 2) to reduce the complexity by pruning the data range of those constraints through the GIS component (GREECE) with respect to the spatial constraints that apply to the potential PV sites. This ensures keeping the whole CPU time reasonably low without losing quality in the final solutions, 3) we show the added value of our approach through a real case empirical evaluation.

In the proposed model, the most suitable solar PV parks are gathered into *rings*, i.e. local aggregates of power plants, connected to one substation. This leads to lower energy unit cost (M€/GWh) as well as means for the decision makers and grid managers to manage their risk adversity, compared to the previous approach. Both approaches are compared, with and without considering constraints from the SONET problem, by applying the GREECE-OPSPV framework to the case of French Guiana. In the context of the French *Energy Transition Act* promulgated in 2015, overseas regions shall reach full energy self-sufficiency by 2030 [27]. Accordingly, it is expected in French Guiana to double or triple RE source capacities by 2023. In this paper, we focus on solar PV energy as it will share 75 % of the volatile RE power to be installed by 2023 [27], but the methodology is being extended to other RE sources.

This article is structured as follows: Section 2 defines the problem, and depicts why and how we revisit the former solar PV park placement approach. In section 3, we introduce the SONET model, and tailor it to specify our new optimization model. Section 4 describes the case study (French Guiana) for which we compared the new SONET-based approach to the former model. Finally, we analyze the results in section 5.

2. Revisiting the optimal solar PV parks placement problem

The seminal GREECE-OPSPV model sought new solar PV plants (location and size) together with their respective substation in a multi-criteria approach. The revisited approach proposed here gathers several power facilities around a common substation to allow for the total cost to be further mitigated. This is especially expected when the maximum power per RE park is constrained by the power grid technical features [28], and thus only small-scale facilities are considered [23]. As we develop below, the smaller-scale strategy has in fact many benefits: it substantially improves both grid operation and risk management once solar PV parks are operating. Along with a method for aggregating plants into power generation clusters, it stands for a very effective solar PV site selection strategy. This study aims at evaluating the foreseen benefits of planning small-scale PV parks for safer grid operation and improved risk management, and to build a computational model to carry out this evaluation.

The overall problem can thus be specified as: Given a set of spatial and temporal data (energy demand, production, potential sites), bounded energy production constraints, determine the optimal selection of small-scale parks (location and sizes), their clusters and optimal set of associated substations to be built, such that the overall installation costs are minimized, the energy supply maximized and the set of constraints hold.

Small scale facilities: a geographical restriction or strategic choice The model and solutions studied in this article, are particularly dedicated to geographical contexts and strategic network management driven by the deployment of small-scale facilities. Indeed, the concept of computing facility clusters around a shared substation has a purpose, and can be deployed.

Before describing our model, let us summarize briefly the different contexts in which one would manage or invest in small-scale facilities :

Safer grid management. When too much intermittent power is injected into the grid, it might be necessary for the network manager to disconnect some of the solar PV parks [23]. When there are only large power plants, the loss of one of them could affect grid stability. The use of smaller facilities therefore gives more flexibility when handling the energy supplied from intermittent sources, and eventually ensures safer grid operation once solar PV parks have been commissioned. Targeting smaller solar PV parks is even more relevant in small not interconnected electricity networks, whose low *inertia* actually implies higher impact from intermittent RE sources on frequency variability and grid stability [28]. By considering smaller PV parks, the risk can still be handled once facilities are operating: whether the riskier solution is chosen or not, the grid manager remains capable of eventually switching off a plant without jeopardizing the whole network.

Park investment and risk adversity. From the point of view of an investor deploying multiple parks, it is actually more interesting to invest in various small-scale facilities rather than in few bigger ones. Since the grid manager will be more concerned by the technical risks than the economical ones, he can shut down any solar PV park in case too much intermittent power is injected into the network [28]. This technical liability might not be related to technical constraints, as it is the case of EDF in French Guiana [29] who can disconnect plants in the chronological order of their connection to the grid [27]. From an investment point of view, the investor may ensure for instance to still have 6 or 7 out of 8 small-scale PV plants running when some parks are potentially disconnected. On the other hand, he could lose half of the production in case he only runs two large-scale facilities. This is an economical risk that some investors might not be willing to take.

Towards future modularity planning. Finally, small-scale solar PV plants offer potential future implementation of extra energy storage facility [30] more straightforward, thanks to both lower nominal power and larger available land within each site. Energy storage allows to smooth the electricity generation from intermittent sources in order to improve grid resiliency, and will likely be increasingly relied upon in the coming years [31]. Smaller facilities therefore ensure further plant modularity and technical flexibility as well as lower economical risk for the investors, even once the PV parks have been commissioned.

3. Adapting the SONET design to RE sources in power systems

In the seminal framework architecture, each solar PV power plant was considered to be built along its own substation. This approach is not sustainable when the number of parks increases substantially, which is the case, when regarding small-scale plants to be built. Thus, we explore the potential through model simulation, of connecting several power plants to the same substation, aiming to combine energy production stability and risk management, with economical savings. However, this leads the existing model to a much higher computational and combinatorial explosion. A key contribution in this article is based on the observation and further implementation of a model that draws from an analogy with a fiber optic network design problem, the SONET problem.

3.1. The SONET analogy

In the field of fiber-optic technology, one of the most popular network designs is the Synchronous Optical NETWORK (SONET) [26]. In one possible topology, each customer is connected to exactly one *local ring* through add-drop multiplexers (ADM), and those local rings are all connected to one *federal ring* through a digital cross connector (DXC) [32]. This topology is depicted in Figure 1(a). The cost of DXCs is much higher than that of ADMs, so the number of DXCs must be minimized, that is the number of rings. This is known as the *SONET Ring Assignment Problem (SRAP) with capacity constraints*. This can be formally depicted as a node-partitioning problem for a given graph G [26]. Nodes of G stand for the customers to be connected and the edge weights represent the traffic demand between sites.

The analogy with power networks is depicted in Figure 1(b) and can be summarized as follows: we may think of the federal ring as the electricity network and of the DXCs as the different substations connected to it. Various power plants can then be connected to each substation/local ring with respect to the available hosting capacity. Those power plants can be of different type, such as dispatchable (biomass, hydroelectricity, geothermal, etc.) and non-dispatchable (solar, wind, etc.) RE sources for example. Each ring may be seen as an aggregate of power plants (i.e. *power generation cluster*) that are spatially *close* enough to each other to be connected to the same substation.

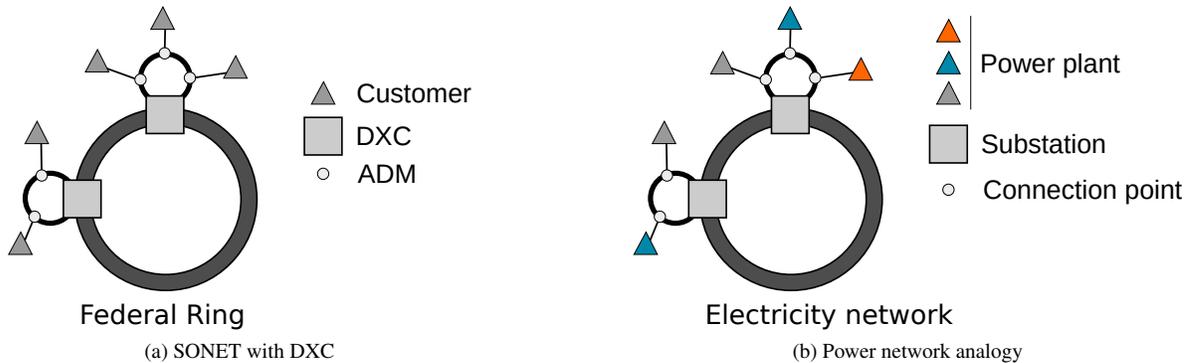


Figure 1: Analogy between SONET typical architecture [32] and power network.

3.2. Problem specification

The new optimization problem formulation, referred to as the *ring approach*, is depicted in Figure 2. The former OPSPV [21] will be referred to as the *park approach* in the rest of the paper.

Given:

Units

Hour (per year) $h \in H = \{1, \dots, 8760\}$ Site index $i \in N = \{1, \dots, n\}$ Ring index $k \in N = \{1, \dots, n\}$

Energy demand and production

Current hourly production from intermittent energy sources (kWh) $Eint_h$ Current hourly production from non-intermittent energy sources (kWh) Eph Estimated global (forecasted) hourly power demand (kWh) Dem_h Nominal power per unit area (kW/m²) $Pnom$

Candidates PV sites

Minimum and maximum *area* for each candidate parcel (m²) $Smin, Smax_i$ Potential Site PS_i Estimated *hourly production* per PV unit (kWh/m²) $Ppv_{h,i}$ Minimal distance from the grid to centroid of a candidate PV site (m) Dg_i

Costs

Transmission line unit cost (€/m) $Clan$ **Find:**The set PS of sites to build a PV plant on allocated among rings of set R ,The surface SA_{ik} to consider for each candidate site PS_i that is selected and belongs to ring R_k **Cost functions:**Sum of all costs of PV installation (Minimize) $Cost = \sum_k (Ccap_k + Cop_k + Ccon_k + Csta_k)$ Capital cost of implementation of new PV power plants (€) $Ccap_k$ Annual operational cost per PV power plant (€) Cop_k Connection costs for each ring of PV power plants, transmission lines (€) $Ccon_k$ Capital cost for new substation per ring (€) $Csta_k$ Total added PV energy production (Maximize) $\sum_k \sum_i \sum_h SA_{ik} \times Ppv_{h,i}$ **Such that the following constraints hold:**

PV existing and added production must be less than 35% of the total energy demand per hour

PV site size cannot exceed maximal given size

PV newly added production plus existing production cannot exceed the total hourly demand

Figure 2: OPSPV updated problem specification (i.e. *ring approach*). See [21] for the former formulation (i.e. *park approach*).

3.3. Model formulation

The generic constraints that relate to the rings for the new PV park placement problem can be derived and adapted from the SRAP, as well as developed to answer specific needs, such as ring diameter and hosting capacity. We specify the creation of specific Boolean variables: Let the Boolean $x_{ik} = 1$ if site PS_i is selected and belongs to ring R_k , and $x_{ik} = 0$ otherwise. In a dual manner, let $y_k = 1$ denote the creation or activation of ring k , if power plants are associated to ring R_k , and $y_k = 0$ otherwise. We introduce d_{ij} , as the distance between site PS_i and site PS_j , and D be the maximum ring diameter. Finally, let c_{ik} be the nominal capacity of site PS_i in ring R_k and C the maximum hosting capacity per substation. A generic mathematical

formulation of the SRAP tailored to the PV park placement problem would be as follows:

$$\min \sum_{k=1}^N y_k \quad (1a)$$

$$\text{s.t.} \quad \sum_{i=1}^N c_{ik} \leq C \quad \forall k, \quad (1b)$$

$$\sum_{k=1}^N x_{ik} \leq 1 \quad \forall i, \quad (1c)$$

$$x_{ik} \leq y_k \quad \forall i, \forall k, \quad (1d)$$

$$d_{ij} x_{ik} x_{jk} \leq D \quad \forall i, \forall j, \forall k, \quad (1e)$$

$$x_{ik}, y_k \in \{0, 1\}.$$

The objective function (1a) seeks to minimize the number of substations. Constraint (1b) states that the total power injected into a substation cannot exceed its maximum hosting capacity C . Constraints (1c) and (1d) that apply to the SONENT problem also apply here [26]. The first ensures that each site only belongs to one ring (1c); the latter guarantees that a ring is active if and only if a site is in fact connected to it (1d). Constraint (1e) imposes that the distance d_{ij} between each pair of PV sites is lower or equal to a given maximum diameter value D , using the idea developed in [33]. To be connected to the same substation, i.e. to belong to the same ring R_k , the sites must be geographically close to each other, that is within the ring diameter.

Though we can make constraint (1e) linear [26], the problem eventually turns out to be intractable due to the combinatorial explosion in the set of potential rings to be considered. To tackle this computational issue, we make powerful use of the GIS GREECE model, to determine pairwise distance between all solar PV potential sites belonging to the set PS . Pairwise distance is derived from the candidates' centroid coordinates. For each ring R_k , we limit the available sites to the set B_k , that is the set of site indices for which sites PS_j are at a distance d_{kj} from site PS_k below a threshold D (including PS_k):

$$B_k = \{j \mid j \in N = \{1, \dots, n\}, d_{kj} \leq D\} \quad \forall k \in N = \{1, \dots, n\} \quad (2)$$

This preprocessing preserves the set of viable solutions without the cost of exploring unrealistic and costly configurations. The ring constraints apply over potential sites for each set B_k , and the constraint (1e) is subsumed by the indices ranging over the sets B_k . Thus, we now define the complete model to be solved, by adding the constraints from the SONENT problem to

revisit the first OPSPV model [21], with respect to the updated specification depicted in Figure 2:

$$\max \sum_k \sum_i \sum_h SA_{ik} \times Ppv_{h,i} \quad (3a)$$

$$\text{s.t.} \quad \sum_{i \in B_k} SA_{ik} \times Pnom \leq C \quad \forall k \in N = \{1, \dots, n\}, \quad (3b)$$

$$\sum_k x_{ik} \leq 1 \quad \forall i \in N = \{1, \dots, n\}, \quad (3c)$$

$$\sum_{i \in B_k} x_{ik} \leq M \times y_k \quad \forall k \in N = \{1, \dots, n\}, \quad (3d)$$

$$M \times \sum_{i \in B_k} x_{ik} \geq y_k \quad \forall k \in N = \{1, \dots, n\}, \quad (3e)$$

$$\sum_{i \in B_k} \sum_h SA_{ik} \times Ppv_{h,i} + Eint_h \leq 0.35 \times Dem_h \quad \forall h, \quad (3f)$$

$$\sum_{i \in B_k} \sum_h SA_{ik} \times Ppv_{h,i} + Eint_h + Ep_h \leq Dem_h \quad \forall h, \quad (3g)$$

$$SA_{ik} \leq Smax_i \times x_{ik}, \forall i \in B_k, \forall k \in N = \{1, \dots, n\}, \quad (3h)$$

$$x_{ik} \times Smin \leq SA_{ik}, \forall i \in B_k, \forall k \in N = \{1, \dots, n\}, \quad (3i)$$

$$x_{ik}, y_k \in \{0, 1\}.$$

Essentially the strategic energy planning over some given time horizon has two main objective functions: 1) to maximize the total hourly energy production over the year through new PV energy generation, 2) to minimize the total costs related to PV installation, maintenance, connection to the grid, etc. As units of these two functions are different, it would not be meaningful to combine both into one single weighted function. Instead, it is solved by seeking the Pareto frontier, i.e. optimizing each function while constraining the other one. As a result, the optimization problem (3a)-(3i) is applied for every given constrained cost value in the range of the Pareto. Aggregate of PV power per ring is kept below a threshold C corresponding to the substation maximum hosting capacity (3b). Constraint (3c) corresponds to previous one (1c) and ensures a selected site only belongs to one ring. Constraints (3d) and (3e) stand for previous equation (1d) and guarantee that a ring with one or more selected PV parks is active. Constraint (3f) prevents the amount of intermittent energy from exceeding 35 % of the total forecast energy demand [34]. Satisfaction of the forecast energy demand is defined by constraint (3g), using existing resources augmented with new PV generation. Constraints (3h) and (3i) relate the size of the PV parks, lying between $Smin$ and $Smax_i$, to whether they are selected or not. This relationship is required to link both the energy production and the different costs. If the size of a plant is not null, then the site is selected; conversely, if a site is not selected then its size is compelled to be null.

Maximize production. First objective is to maximize the PV production (3a), where $Ppv_{h,i}$ can take the best or worst case value depending on the scenario at hand:

$$\sum_k \sum_i \sum_h SA_{ik} \times Ppv_{h,i}$$

Minimize costs: Modeling non-linear functions. In the *ring approach*, the total cost $Cost$ corresponds to the sum of the costs in every ring R_k . Each cost in R_k is the aggregate of the capital cost Cap_k of all the PV parks built in the ring, plus the connection cost to the grid $Ccon_k$, the substation cost $Csta_k$ and the operational & maintenance costs Cop_k :

$$Cost = \sum_k Cap_k + Cop_k + Ccon_k + Csta_k \quad (4)$$

Capital cost Cap_k and operational & maintenance costs Cop_k are defined as piecewise linear functions, and depend on the nominal power range of the PV parks implemented in ring R_k . It is illustrated below for Cap_k but Cop_k follows the same

pattern with different coefficients:

$$Cap_k = \begin{cases} a_1 \times Pnom \times (\sum_i SA_{ik}) + y_1 & \text{if } 0_{MW} \leq (\sum_i SA_{ik}) \times Pnom \leq 1_{MW} \\ a_2 \times Pnom \times (\sum_i SA_{ik}) + y_2 & \text{if } 1_{MW} \leq (\sum_i SA_{ik}) \times Pnom \leq 10_{MW} \\ a_3 \times Pnom \times (\sum_i SA_{ik}) + y_3 & \text{if } 10_{MW} \leq (\sum_i SA_{ik}) \times Pnom \end{cases} \quad (5)$$

Regarding connection costs $Ccon_k$, using the centroid of all sites as the connection bridge to the parks would in fact make the problem nonlinear. To keep linearity, we have thus considered in first approximation the maximum distance to the grid among PV parks implemented in ring R_k :

$$Ccon_k = Clan \times \max_{i \in B_k} (dg_i \times x_{ik}) \quad \forall k \quad (6)$$

where $Clan$ stands for the unit cost of transmission lines (€/km). Finally, following the same idea as for the plant capital cost, we also define the substation cost $Csta_k$ as a piecewise function. The piecewise model allows for the problem to remain linear and for economies of scale in building substations to be included into the analysis. The substation cost depends on the aggregated PV nominal power in ring R_k , which actually determines the final substation hosting capacity:

$$Csta_k = \begin{cases} a_4 \times Pnom \times (\sum_{i \in B_k} SA_{ik}) + y_4 & \text{if } 0_{MW} \leq (\sum_{i \in B_k} SA_{ik}) \times Pnom \leq 10_{MW} \\ a_5 \times Pnom \times (\sum_{i \in B_k} SA_{ik}) + y_5 & \text{if } 10_{MW} \leq (\sum_{i \in B_k} SA_{ik}) \times Pnom \leq 50_{MW} \\ a_6 \times Pnom \times (\sum_{i \in B_k} SA_{ik}) + y_6 & \text{if } 50_{MW} \leq (\sum_{i \in B_k} SA_{ik}) \times Pnom \end{cases} \quad (7)$$

4. Case study: ring vs. park approach in French Guiana

In this paper, we have applied both SONET-based ring approach and park approach in French Guiana, according to characteristics and policy targets for the horizon 2030 in the region. In the context of the French *Energy Transition Act*, it is expected to triple RE source capacities by 2023 [27], first by increasing solar PV, then biomass.

4.1. Data and GIS processing

The GIS GREECE model is extensively depicted in [22] and [21]. This section comprises a summary of the underlying data and its processing, for proper understanding of the analysis.

4.1.1. Potential PV sites

The spatiotemporal GIS GREECE model first extracts the potential sites that will feed the optimization module depending on geographical constraints and land management. The model prunes the unrestricted territory in order to finally get suitable parcels with respect to minimum and maximum surface area. Restriction layers have been fetched from different world [35] and national geographic databases (such as ONF 2015 [36] and 2017 [37], or IGN [38]). Buffer values around restricted areas have been retrieved from the literature and are depicted in [21]. We have considered a *permissive* land management scenario, for which the size of these buffers has been minimized in order to maximize the number of potential candidates. Threshold distance values from both the electrical grid and road network have been taken equal to 20 km. It is converted into buffer layers beyond which PV sites cannot be extracted. Finally, the available land is derived from intersecting all these layers, and is partitioned using graph partitioning theory [39] along with a honeycomb mesh, according to minimum and maximum surface area of 1.5 Ha and 50 Ha respectively. It has resulted in a set PS of 133 land parcels, depicted in Figure 3, corresponding to as much potential sites where solar PV plants could be built. We will rely on those plots to compare both ring and park approaches.

Beyond geographic location, each potential site generated by GREECE also comes along with specific features and resource time series (e.g. solar irradiation). Those features are extracted from heterogeneous data layers and remote sensing data such as geographic databases, digital elevation models (DEM) or else satellite images. Essentially, GREECE allows for *de-spatialization* and discretization of the potential sites in order to feed the combinatorial optimization model with *items* defined as tuples of digitalized attributes. Each candidate item PS_i from set PS is represented by static (e.g. area, shape, distance to the grid, slope, land use, etc.) and dynamic (e.g. time series of resource values) attributes (see Table 1 in [21] for an example of feature attributes). Eventually, all or some of those attributes might be used as constraints or function costs in

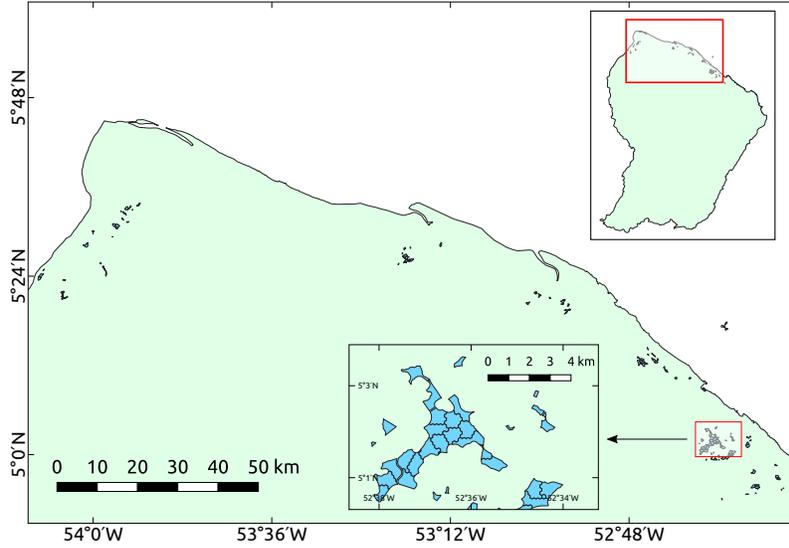


Figure 3: Set of potential sites derived by the GREECE model in French Guiana.

the optimization module with respect to the decision maker’s criteria. In the present study, we typically passed on land surface area, distance to the grid, and time series of solar irradiation values to the optimization model, which then converts those values into maximum nominal power, connection costs, and solar PV plant output power profiles. Depending on the application, further constraints or function costs might also be derived from other parcel attributes such as land use and topography. We here did not consider those extra features for simplicity purposes.

4.1.2. Solar irradiation and PV output power

When providing potential sites to the optimization model, GREECE also feeds each of them with corresponding PV output power hourly time series. First, solar irradiation time series are aggregated within each parcel using satellite-based solar radiation maps. Originally, as French Guiana solar maps were only available at a monthly time step [40], we made use of modified synthetic generation models [41] in order to estimate daily [42] and then hourly profiles [43]. Note that we only generated those patterns because of the original monthly resolution of the solar radiation products over the region. Ideally, one would directly use satellite-based solar radiation data at daily or hourly scale, as our model can fully take advantage of spatiotemporal remote sensing data at high temporal resolution.

After having generated solar irradiation time series, solar PV output power is derived using the conversion model developed by the Sandia National Laboratory [44]. It is based on the California Energy Commission (CEC) 6-parameter model [45] and the corresponding PV module I-V curve defined according to the single-diode cell model:

$$I = I_L - I_0 \left[\exp \left(\frac{V + IR_s}{nN_s V_{th}} \right) - 1 \right] - \frac{V + IR_s}{R_{sh}} \quad (8)$$

I and V are the output current and voltage respectively, I_L is the photocurrent, I_0 the saturation current, R_s the series resistance, R_{sh} the shunt resistance, n the diode ideality factor, N_s the number of cells in series, and V_{th} the thermal voltage of the cell. This model is analytically solved using the Lambert W-function [46].

All parameters I_L , I_0 , R_s , R_{sh} and the product $nN_s V_{th}$ are derived from PV module reference parameters (a_{ref} , $I_{L,ref}$, $I_{0,ref}$, R_s , $R_{sh,ref}$ and Adjust) based on the CEC model [45], and exogenous factors standing for weather and climatic conditions, that is solar radiation, ambient temperature, wind speed and albedo [44]. In first approximation, we have considered typical constant values for temperature, wind speed and albedo [21]. Solar radiation in module’s plane has been derived from global horizontal irradiance (GHI) divided into its beam and diffuse components according to the Erbs diffuse fraction model [47]. CEC reference parameters for the PV module we used in this study are given in Table 1. The PV output power is eventually retrieved based on the maximum power point (MPP), that is by retrieving the maximum of the I-V product function through golden-section search [44].

Finally, as the size of each power plant is an optimization variable, our approach is based on power facilities defined as any gathering of several *PV units*. Each PV unit is defined as several strings of modules having specific tilt, azimuth and land usage, and connected to an inverter. Every solar PV plant characteristic (size, nominal capacity, etc.) is eventually summed up over all units it is made of. Features of the PV unit used in this study are given in Table 2.

Table 1: CEC reference parameters for the PV module considered in this study [44].

a_{ref}	1.53 V
$I_{L,ref}$	9.65 A
$I_{0,ref}$	$6.51 \cdot 10^{-11}$ A
R_s	0.21 Ω
$R_{sh,ref}$	2213.14 Ω
Adjust	1.84 %

Table 2: Characteristics of one PV unit used in energy simulation.

Nominal power (P^*)	6 kW
Number of modules	20
Module efficiency	18.05 %
Inverter power	5 kW
PV-to-inverter ratio	1.2
Array tilt	Site latitude
Array azimuth	180°
Total module area	32.0 m ²
Land usage (A_{mod})	106.7 m ²
$P_{nom} = P^*/A_{mod}$	0.056 kW/m ²

4.1.3. Cost function parameters and values

As depicted in Figure 2, the optimization model seeks the best compromise between maximizing PV production and minimizing the various related costs. We typically divided those costs between fixed unit costs and variable costs defined as piecewise linear in order to keep linear tractability. Set up of transmission lines for connection from potential PV plant to the grid are taken as a fixed unit cost, equal to 1000 €/m according to EDF specifications. All the other costs are regarded as piecewise, that is PV park capital cost Cap_k , operation & maintenance costs Cop_k , plus the substation installation cost $Csta_k$ (equations (5) and (7)). Piecewise coefficients for Cap_k and Cop_k were formerly derived from [48] and are summarized in Table 3. Coefficients used to compute the substation cost $Csta_k$ are specific to the present study: they have been retrieved from [49] and are depicted in Table 4.

Table 3: PV plant capital and annual operation cost piecewise parameters [48].

New PV power plant capital cost (Cap_k)		Annual operation costs (Cop_k)	
Slope a_n (€/kW)	y_n value (€)	Slope b_n (€/kW)	y_n value (€)
$a_1 = 2701$	$y_1 = 0$	$b_1 = 19$	$y_1 = 0$
$a_2 = 1800$	$y_2 = 901,000$	$b_2 = 16$	$y_2 = 3000$
$a_3 = 1200$	$y_3 = 6,901,000$	$b_3 = 10$	$y_3 = 63,000$

Table 4: PV plant substation capital cost piecewise parameters [49].

Substation cost (C_{sta_k})	
Slope a_n (€/kW)	y_n value (€)
$a_4 = 43.7$	$y_4 = 0$
$a_5 = 13.98$	$y_5 = 297,200$
$a_6 = 13.11$	$y_6 = 340,700$

4.2. Forecast energy production and demand

Forecast data for the horizon 2030 have been drawn from the 2016 existing production and consumption data [29]. Regarding solar PV penetration planning in the French Guiana’s power network, we relied on the assumption that the current production remains stable and is maintained. Then we considered the worst case scenario in the increasing power demand based on the EDF forecasting study [34]. This scenario assumes a 5% annual growth from 2016 consumption data [29]. Fig. 4 illustrates the daily hour variations over 2030 and projection of the demand for that scenario. Regarding potential PV production on each candidate site, we derived forecast GHI data from current ones through a static projection.

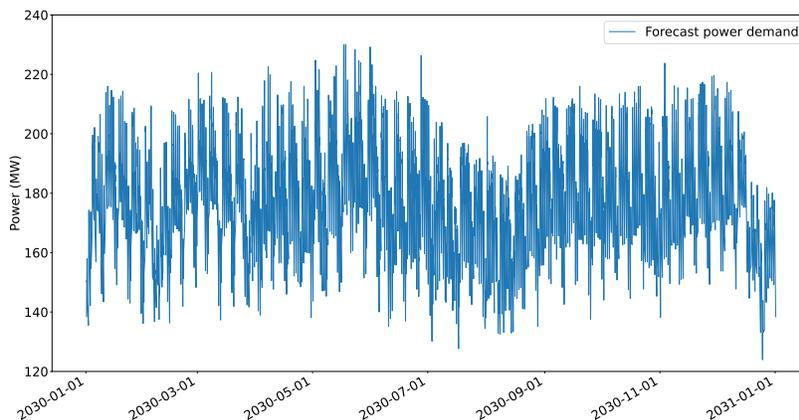


Figure 4: EDF-based worst case scenario for 2030 forecast power demand over daily hours.

5. Results and analysis

In this section, the emphasis is placed on comparing the results from the new SONET-based model (*ring approach*) against those of the former GREECE-OPSPV model (*park approach*). GREECE was originally implemented in Python using libraries depicted in [22] and [21], and led to the extraction of 133 potential sites along with their digitalized attributes (see section 4.1.1). Corresponding data items were then implemented into both former and updated (SONET-based) OPSPV module (see Figure 2). We run different numerical experiments aiming at maximizing PV generation and minimizing the totals costs. We finally derived Pareto charts of compromising solutions by computing maximum energy amounts over multiple cost thresholds.

5.1. Park vs. ring spatial distribution: economical benefits and risk management

In this section, we compare the main aspects of relevance to the decision maker and network manager (power plant energy investors in French Guiana and EDF) between the GREECE-OPSPV model (park approach) and our proposed SONET-based model (ring approach), that is economical performance and risk management. The comparison is based on the worst case scenario of the RO approach. In all cases, we only consider rings made of small-scale facilities whose nominal power is not greater than 5 MW. We first compare Pareto solutions for both approaches (Figure 5) in two fair distinct cases: (a) only small-scale facilities up to 5 MW can be built in the park approach, while no limitation is set on the ring hosting capacity (i.e maximum power that can be injected into the corresponding substation, sum of all PV parks’ power attached to that ring);

(b) solar PV parks up to 20 MW can be built in the park approach, and so the same applies to ring hosting capacity in the ring approach, which cannot exceed 20 MW as well. The 20 MW limit corresponds to the specific technical constraints of the French Guiana power network [34]. This comparison investigates the relative contribution of each approach with respect to economical benefits (a), and risk management (b) in terms of spatial distribution of the parks.

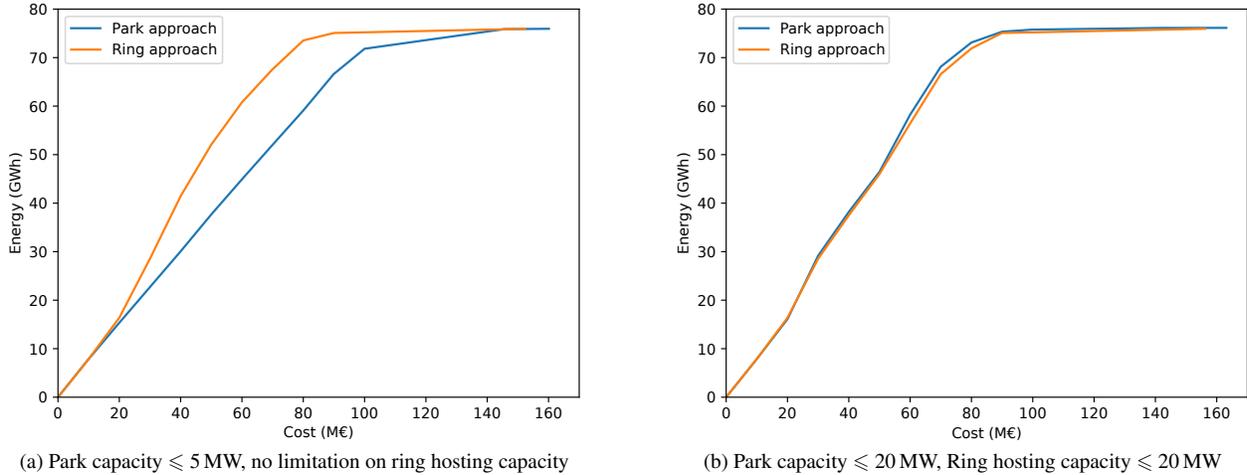


Figure 5: Pareto solutions for ring and park approach. Rings are composed of small-scale facilities (≤ 5 MW).

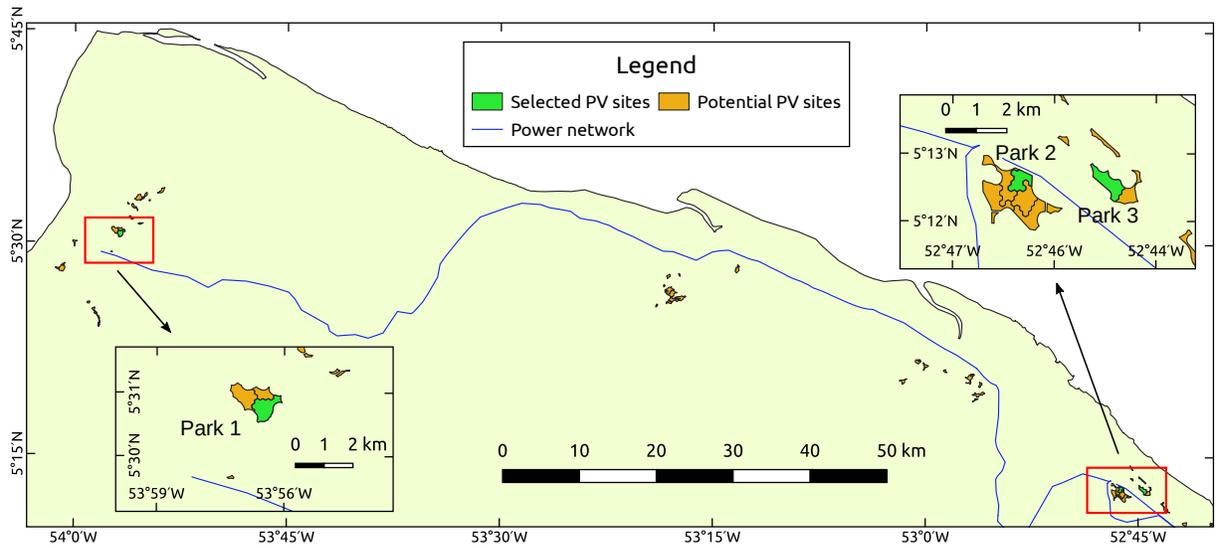
When only small-scale solar PV parks can be integrated into a power network (a), the Pareto solutions depicted in Figure 5(a) show that the ring approach consistently gives better results in terms of economical benefits, with for instance 10 MW of extra installed power and 16 GWh of extra power generation for the same overall cost (60 M€). We didn't set any limitation on the ring hosting capacity, so that this gain should be regarded as the maximum economical benefit we can theoretically expect in that specific case (PV parks up to 5 MW). When both approaches are subject to the same technical constraints (b), the resulting Pareto solutions remain similar regardless of the cost value (see Figure 5(b)). This is coherent as the number of rings in the *ring approach* will now correspond to the number of parks in the *park approach*, resulting in the same number of substations in both cases. In summary, while these Pareto curves show how park and ring approaches perform economically, it tells us nothing about how they both perform in terms of risk management. To do so, we must look at the spatial distribution and resulting temporal production of the corresponding facilities.

To describe the resulting spatial difference between both models, we plot in Figure 6 the selected PV sites against the selected rings regarding case (b) and with respect to the same Pareto solution (cost value = 80 M€). In both park and ring configurations, the selected PV sites are scattered throughout the Northern shore of French Guiana, along the power network (i.e. cost is lower for sites close to the grid). The total installed power is similar (45.4 MW against 44.9 MW) but is allocated among 3 facilities in the park approach (Figure 6(1)), and among 3 rings and 11 small-scale facilities in the ring approach (Figure 6(2)). The characteristics of the PV parks in both approaches are given in Table 5 and Table 6.

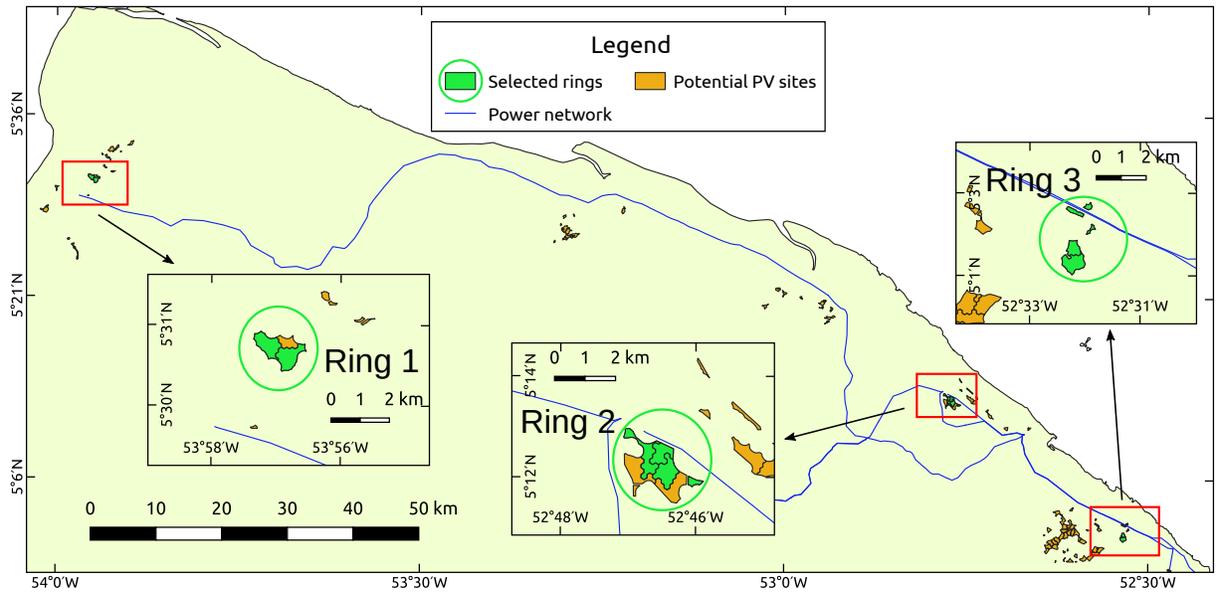
Table 5: Characteristics of the solar PV parks depicted in Figure 6(1)

Park ID	Nominal power (MW)
Park 1	6.87
Park 2	18.52
Park 3	20
Total	45.39

Hourly output power profiles over the year for both examples of Figure 6 are given in Figure 7. This solution is very illustrative as the distribution of the nominal power among parks and rings is rather similar. Accordingly, in the ring approach



(1) Selected PV sites in *park approach* (Park capacity ≤ 20 MW)



(2) Selected rings in *ring approach* (ring hosting capacity ≤ 20 MW)

Figure 6: Park (1) vs. ring (2) approach spatial results for Pareto solution of Figure 5(b) (selected cost value = 80 M€).

Table 6: Characteristics of the rings depicted in Figure 6(2)

Ring ID	Number of parks	Nominal power (MW)	Park capacities (MW)
Ring 1	2	5.56	{4.72, 0.84}
Ring 2	4	19.3	{5, 5, 4.74, 4.56}
Ring 3	5	19.99	{5, 5, 5, 2.8, 2.19}
Total	11	44.85	—

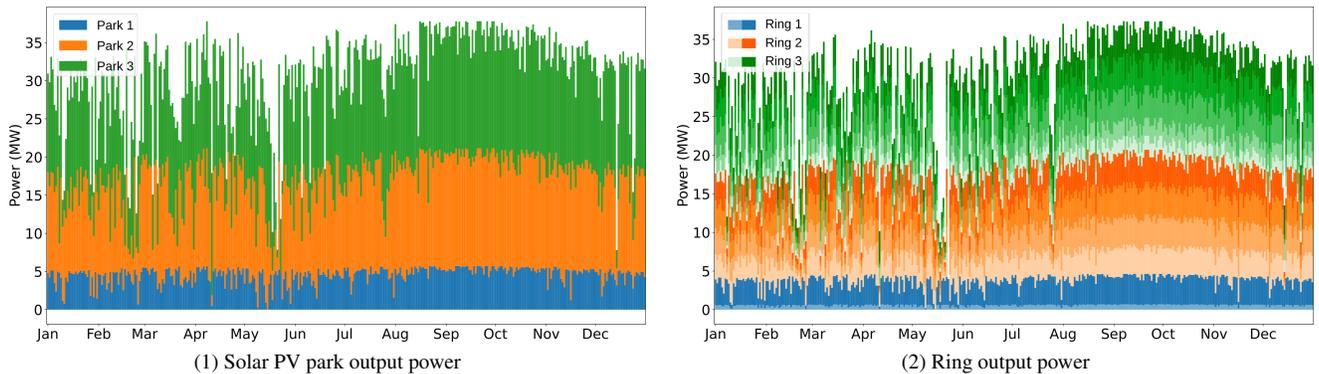


Figure 7: Park (1) vs. ring (2) approach output power for Pareto solution of Figure 5(b) (selected cost value = 80 M€). For the ring approach, each power profile is broken down into its PV park components (one color gradient per ring).

(Figure 7(2)), the optimization model aggregates small-scale PV parks into power generation clusters (i.e. rings) whose aggregated profile through the year is close to that of standalone parks in the first case (Figure 7(1)). All ring output power profiles depicted in Figure 7(2) are represented as stacked bar plots of the solar PV park profiles that constitute them (see Table 6). We thus observe that whenever a facility is disconnected by the network manager in either the first (Figure 7(1)) or the second configuration (Figure 7(2)), it will affect stakeholders differently. In the ring configuration, it results in *gradually* decreasing the power injected into the network at any time, while each disconnection in the park configuration might result in substantial power drops. Hence the park configuration could be a greater threat to the power grid, potentially resulting in greater challenges for the network manager. Which is equally true for the investors, as potential disconnections also induce greater risk adversity: economical impact grows along with the range of the power drop. Conversely, this impact is *gradually* mitigated when disconnections occur in the ring configuration, even if co-investment is considered (i.e. the smaller scale mitigates the economical impact of any potential disconnection). It corroborates what we previously stated in section 3, namely that small-scale power stations should allow for safer grid operation as well as better risk management once it is operating. Though Pareto solutions remain similar in case (b) (see Figure 5(b)), the ring approach therefore remains the best energy planning strategy when considering both the decision maker and the network manager needs.

6. Conclusion

In this article we have proposed a new model to simulate and study the potential benefits of planning rings of small PV parks through different scenarios. The contribution is both at the model level, through the analogy with the SONET problem addressed in fiber networks, and with respect to the insights gained on the scenarios outcome analysis. Indeed we have shown how solar PV site selection can efficiently be combined with the optimization of the connection to the grid in terms of operational costs. The GIS and optimization integration models have built on the spatiotemporal data and constraint integration drawn from the former GREECE-OPSPV model. The ring-based model enables to build scenarios whereby the selected potential PV sites can be aggregated around one shared substation that feeds the power grid. Our experimental study is based on the contextual assumption of planning small-scale PV sites. The model outputs show that the ring-based configuration consistently enhances economical performance, and when compared to the former approach the results show substantial gains in costs per kWh produced. We also show that the reduced scale authorized by the *ring configuration* improves energy stability of the solutions, which results in mitigating the risks for both the network manager and the decision maker. Overall, our proposed SONET-based model provides an enhanced set of solutions to the stakeholders involved in energy transition (investors, policy makers, network manager, etc.), and therefore contributes to designing optimal energy planning strategies.

Based on our previous study [21] and the present work, we have shown that the GREECE-OPSPV decision support framework combined with the SONET-based model performs well in estimating the risk adversity of RE planning and management. It is intended to help future RE policies to take into consideration those risks and implement optimal solutions accordingly. From our findings, it is clearly recommended for those policies to support smaller-scale RE planning strategies, given that the

small-scale definition will depend on the total intermittent RE power that could actually be injected into the corresponding power grid.

In terms of future work, the SONET-based strategy can bring forward new possible scenarios for site selection of heterogeneous RE sources (dispatchable and non-dispatchable) at utility scale. Operational costs of RE mix penetration in a given region might be reduced further by spatially aggregating the corresponding facilities within local clusters/rings. Accordingly, ongoing work includes the extension of our GIS and optimization model to assessing biomass potential and its energy source embedded along with solar PV into the power grid. This extension can also contribute to bringing stability in the network, but potentially at a substantial technical cost. Thus investigating how we can combine the strengths of cost and network stability brought by the PV ring approach, with a biomass extension (storage, combustion, connection) is of high interest.

Acknowledgments

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