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A Parametric Genetic Algorithm Approach to Assess Complementary Options of Large Scale Wind-solar Coupling

Tim Mareda, Ludovic Gaudard, and Franco Romerio

Abstract—The transitional path towards a highly renewable power system based on wind and solar energy sources is investigated considering their intermittent and spatially distributed characteristics. Using an extensive weather-driven simulation of hourly power mismatches between generation and load, we explore the interplay between geographical resource complementarity and energy storage strategies. Solar and wind resources are considered at variable spatial scales across Europe and related to the Swiss load curve, which serve as a typical demand side reference. The optimal spatial distribution of renewable units is further assessed through a parameterized optimization method based on a genetic algorithm. It allows us to explore systematically the effective potential of combined integration strategies depending on the sizing of the system, with a focus on how overall performance is affected by the definition of network boundaries. Upper bounds on integration schemes are provided considering both renewable penetration and needed reserve power capacity. The quantitative trade-off between grid extension, storage and optimal wind-solar mix is highlighted. This paper also brings insights on how optimal geographical distribution of renewable units evolves as a function of renewable penetration and grid extent.

Index Terms—Energy optimization, grid integration, genetic algorithm, optimal spatial distribution, power system modeling.

I. INTRODUCTION

Future highly renewable power system is foreseen to integrate a significant contribution from wind turbines and solar photovoltaic (PV) electricity [1] although both energy sources exhibit strong variability related to their weather-driven nature. Integration of intermittent generation into the electric network is a challenging task as supply must always match demand. Balancing requirements are usually supported by adding reserve capacity in the form of quickly adjustable backup power plants (BPP), operating for example on gas. Because of variable renewable energy sources (VREs) overall low reliability and lack of flexibility, a highly renewable power system is likely to necessitate huge amounts of such backup units whereas conventional baseload generation will vanish [2]. Adding energy storage capacity is of course another way to maintain the systems’ equilibrium and has the advantage to allow time domain transfer of excess VREs generation.

Another possible integration strategy is to spatially extend the power system [3]–[6]. Present power systems are mainly designed within meso-scale areas, e.g., related to territorial boundaries, around dispatchable and centralized supply units in proximity to load centers. Another important feature introduced by VREs is distributed generation (DG) which entails deep structural changes in network dynamics. Facing a fast growing share of VREs generation the European transmission grid is already showing weaknesses as large scale interconnections are more and more solicited by widely spread fluctuating in-feeds. Following the authors of [7] a strong pan-European transmission backbone appears to be a necessary condition for further VREs deployment.

As far as quantity is concerned some locations are best suited than others for VREs units siting. Although, past the tipping point where renewable power exceeds the load it becomes unclear if it is not more beneficial to favor quality over quantity, i.e., to favor a set of dispersed locations that minimize the supply-demand mismatch. This question is also related to BPP and storage optimal sizing and is at the heart of the present study. More precisely this paper introduces a simple yet effective methodological framework which explicitly investigates the interplay between storage, balancing needs and optimal geographical dispersion of VREs generators.

As an introductory example, let us consider the optimal allocation problem of deploying efficiently a given VREs power capacity with respect to a time-varying consumers’ load. At large enough grid scales there should be spatial and technological distributions of VREs units that are better than others to match demand. Taking a social planner point of view there is in fact a fundamental ambiguity on defining what is optimal. A first option would be to seek a spatial distribution of units that favor smoothness and thus minimize BPP power rating. This makes sense in practical terms as it is economically undesirable to secure every gigawatt (GW) of renewable power by an equivalent amount of BPP capacity. Another option would be to maximize renewable penetration, i.e., minimize BPP output, which is preferable when it comes to power system sustainability and efficient VREs load factors.

In essence once renewable capacity is in peaking range the question of quantity versus quality becomes relevant, where quality must be understood here as the ability to match demand. This said it is likely that any optimal distribution...
will strongly depend on defining parameters such as the size of accessible space for unit deployment, the power gap between peak load and aggregated rated power of renewable units as well as the existing storage capacity within the system. Our analysis will show that there are several threshold effects that have to be accounted for.

The main goal of this study is to investigate how will evolve grid and storage integration options within growing VREs capacities. In order to do this we use an optimal distribution search algorithm in combination with a parametric physical simulation of hourly power mismatches between supply and demand. As a case study the Swiss electricity consumption is related to varying extents of transmission grid, thus specifically exploring how overall performance is affected by the definition of transmission network boundaries. Switzerland is geographically well centralized in Europe and already a crossing point of growing interregional power flows. It also happens to be on the way of nuclear phase out, which represents about a third of actual electricity production. How to replace this power capacity is still under examination and notably raises questions about the possible building up of electricity importations [8]. At the local level hydropower is the main renewable source at disposition, but it has already attained its deployment limit. Accumulation dams still offer electricity storage prospects such as illustrated by the important “Nant de Drance” pumped-hydro project which will be able to deliver a power rating of 900 MW [9]. Further renewable power deployment in Switzerland is anticipated to rely mainly on distributed solar PV. Although we look into a specific case, narrowing underlaying hypothesis, this work has a more general scope in that it is addressing the local versus global debate surrounding the ongoing power system transformation of all European countries.

The paper proceeds as follows: in Section II we review related work. The model is described in detail in Section III. Results and discussions are developed in Section IV before concluding in Section V.

II. EXISTING LITERATURE

Scenarios with close to 100% renewable production are investigated in numerous studies within a wide range of methodological frameworks and geographical boundaries. Some carry out advanced operational and economic modeling [1], [10]−[13], while others concentrate on fundamental systemic aspects of VREs integration in order to gain a better understanding of existing options, opportunities and threats [5], [6], [14]−[16].

The role of storage in prospective power systems has naturally drawn a lot of attention in the energy research community as flexibility and curtailment losses issues are building up [2], [6], [15], [16]. Among others Rasmussen et al. [15] explore the interplay between storage sizing, solar-wind optimal mix and balancing needs in an idealized pan-European power system. Existing literature on energy storage is reviewed in depth by Zucker et al. [17].

A number of contributions investigate the statistical correlations of distributed wind and/or solar energy supply. According to Heide et al. [18] there is an interesting seasonal complementarity between wind and solar resources over Europe. Optimal mix considerations should thus be accounted for when looking at systemic VREs integration. Considering the Italian territory the authors of [19] investigate the statistical correlation between solar and wind energy supply, while the authors of [20] look at complementarity options for the Ontario (Canada) region. The authors of [21] introduce a probabilistic methodology to integrate stochastic wind power inflows into transmission load analysis. The work presented in [22] explores the smoothing effect of an European-wide grid on wind power output.

Benefits of global electricity grid deployment for VREs integration has been examined in [23]. More recently the influence of European transmission grid reinforcements has been deeply analyzed from a technico-economic perspective in various studies [3]−[6], [13]. The authors of [3] introduce an investment and dispatch optimization model to explore grid extension strategies considering least-cost objectives. It is shown that large scale grid interconnection is essential in order to achieve a cost-efficient highly renewable power system. Schaber et al. [4] use a regionally resolved technico-economic model to analyze how grid extensions interact with electricity market in Europe within projected VREs penetration for 2020. Future transmission network design is foreseen to have substantial impact on price dynamics as well as conventional generation power plant operation. In [5] a similar methodological set up has been used but to investigate grid extension as a function of wind and solar penetration and optimal mix. The interplay between backup energy demand and storage capacity is evaluated within transmission constraints in [6] while the authors of [13] presents a large-scale spatial model of the European electricity market intended to analyze the effects of load flow congestion regarding investments strategies and market design, considering a social welfare maximization objective.

The main original contribution of this paper is to explicitly derive highly resolved optimal spatial distribution of VREs units using a parametrized search algorithm approach, spanning varying prospective power system designs. The goal is to investigate the intertwined scaling effects of both storage deployment and grid extension on the transitional path towards a highly renewable power system. We believe that our explicit approach has never been presented in scientific literature and has practical interest for a transparent evaluation of VREs integration options at a system level. In contrast with the techno-economical approach developed in e.g., in [3]−[6], [13] we stay focused on the physically driven dynamics. Our geographically centralized case study approach also differs from more general assessments, as for instance in [2], [15]. By taking this narrower point of view we intend to reduce underlying hypothesis and complexity to get robust order of magnitude from a well-defined perspective. We think this will contribute to shed light on important dynamical patterns, helping to achieve an efficient integration of weather driven power supply. Our contribution also provides an effective methodological approach to the system wide optimal spatial distribution problem that can be implemented in more advanced modeling.

III. METHODOLOGY

The backbone of our methodology relies on a parameterized weather-driven simulation model of hourly power mismatches
between generation and load. This basic modeling tool is designed to evaluate the overall performance of a given spatial distribution of renewable units. It is associated with a heuristic optimization process, namely a genetic algorithm, in order to find the near-optimal distribution of VREs units over a specific territory. Later, we will present how these elements exactly interact but first start with the fundamental building blocks of our methodological design.

A. Grid and Load

In this study the Swiss aggregated electricity consumption will serve as our demand side reference. 15 minutes end user load data were obtained from the national transmission system operator Swissgrid (www.swissgrid.ch) and from which is computed the hourly load time series \( L(t) \).

Our first objective is to simulate the weather-driven electric generation delivered by a given set of spatially distributed solar and wind generators. Power system simulations are conducted on a 3 years period (2003–2005) and based on hourly time-series of wind and PV electricity output calculated for each cell of a 0.75° grid covering Europe (Fig.1). In order to reduce modeling complexity meteorological conditions are supposed to be homogeneous on the whole surface of each cell. This assumption is fairly realistic for solar potential, less so for wind where landform has its importance. However the purpose of our work is to highlight the driving dynamical patterns involved at an aggregated system level. As such the use of a representative VREs potential seems justified. It is yet possible that with better resolution results would partly differ. VREs generators are uniquely localized by their cell coordinate \( x = 1, 2, \ldots, N \), where \( N \) is the total number of cells on the spatial footprint. Cells that contain less than 30% of land are discarded which allows only near coast wind offshore generation.

In order to take into account electricity transmission limitations our spatial representation integrates the European high voltage transmission grid provided by ENTSO-E (www.entsoe.eu [7]). Furthermore we assume shortest path connection between each cell center and the nearest high voltage line (Fig. 1). Swiss electricity consumption is assumed to be geographically concentrated on a single node represented by the central dot in Fig.2 where all distributed VREs generation is routed. Grid extension is then defined by selecting all cells within a distance \( R \leq R \) of the load center, this distance being calculated along transmission lines shortest path. Formally, for any distance \( R > 0 \) the set \( \chi_R \) of accessible sites is defined as \( \chi_R = \{ x \leq N \mid d_T(x, x_0) \leq R \} \) where \( d_T(x, x_0) \) is the topological shortest network distance between the \( x \) cell center and the load center \( x_0 \).

Transmission losses are also accounted for by reducing delivered energy at a rate of \(-4\%\) per 1000 km of transmission path in accordance with Schaber et al. [5]. However we assume no congestion or power flow limitations, i.e., transmission lines load capacity is unconstrained within the \( \chi_R \) grid extension.

The smallest grid extent is limited to the Swiss territory. The distance then extends by 300km steps along transmission lines.

B. VREs Output Dataset

The next step is to derive, for both wind and solar resources, a tempo-spatial VREs hourly power output dataset. Formally we derive for each cell on the spatial footprint a resource specific hourly electricity generation time-series based on highly resolved reanalysis data.

PV energy output depends primarily on the amount of incident solar radiation received which in turn is a function of the geographical location and plane orientation of the module as well as atmospheric conditions. For the present study we assume generic PV cells characterized by a global conversion efficiency of 13%. We also assume PV modules to be fixed, ideally oriented south and tilted at latitude angle in order to maximize in-plane irradiation over the year.

Solar electricity output is calculated using hourly mean of horizontal-plane surface incoming shortwave (SIS) radiation available from the Climate Monitoring Satellite Application Facility (CM SAF, www.cmsaf.eu [24],[25]). The SIS data set is given at 0.03° spatial resolution on the METEOSAT footprint and has been extensively validated [26]. This ground level mapping of solar radiation is essentially based on the Heliosat method and takes into account atmospheric conditions. Single hourly irradiation value per pixel is calculated.
by simple averaging on each cell surface. Next, a set of standard geometrical transformations which is based on geodetic considerations is used to compute from the given horizontal-plane values an effective tilted-plane incident irradiation per square meter of PV cell. Considering that each square meter of PV cells correspond roughly to 0.15 kWp of rated power we end up with a solar generation matrix \( PV \in M_{N \times T} \) which specifies for each pixel of spatial coordinate \( x \) that \( 1, \ldots, N \) and for each hourly time increment \( t = 1, \ldots, T \) the potential solar power output per \( MW_{peak} \) installed.

Cell specific hourly wind power generation is evaluated using the European Center for Medium-range Weather Forecast (ECMWF, www.ecmwf.int [27]) ERA-interim reanalysis database [28]. Longitudinal and latitudinal wind magnitudes time-series are available from the ECMWF at 0.75° spatial resolution and 6 h time increment. An hourly wind vector field has been derived from existing data. The power curve of a given wind turbine is an important characteristic as it specifies how much energy can be harvested from different wind conditions. For this study we consider a generic 3 MW V112 wind turbine from the Danish manufacturer Vestas [29] which is representative of today’s deployed technology. Hourly wind magnitudes derived from the ECMWF dataset are thus applied on the V112 power curve and subsequently normalized as to obtain the potential wind power generation matrix \( W \in M_{N \times T} \).

C. Power System Parametrization

The power system sizing is defined according to the four following parameters:
1. \( P_{ren} \): The aggregated rated power of renewable units.
2. \( R \): The spatial extent of transmission grid.
3. \( C_s \): The storage energy capacity within the system.
4. \( \zeta \): The storage power capacity (charge and discharge).

We assume that the total renewable power \( P_{ren} \) is evenly divided over \( k \in \mathbb{N} \) units of power \( P_{ref} \), such that \( P_{ref} = \frac{P_{ren}}{k} \). Generally speaking these units are either PV arrays or wind turbines and distributed on the territory defined by the spatial extent parameter \( R \). A specific renewable unit deployment is then described by a set of \( k \) couples \( I_{k,R} = \{ (x_1, \text{type}_1), (x_2, \text{type}_2), \ldots, (x_k, \text{type}_k) \} \) where \( x_i \in \chi_R \) indicates the location of unit \( i \) and \( \text{type}_i \in \{ \text{pv}, \text{wind} \} \) its technological type. Note that there is no restriction on the number of units a given cell can contain, which means spatial concentration of generators is possible up to \( P_{ren} \), although the number of units \( k \) has to be defined and will fix the degrees of freedom of the sitting process (see Sections III-F and IV).

D. Simulation Model

Given a set of distributed VREs generators \( I_{k,R} \), our first task is to evaluate renewable energy penetration. As our focus is on solar and wind energy integration we will assume they have priority to cover demand. Within the fundamental constraint of supply-demand equilibrium, balancing needs are determined by the hourly power mismatch \( \Delta_t \) for each time increment \( t = 1, 2, \ldots, T \) such that

\[
\Delta_t := P_{ref} \left[ \sum_{x \in I_w} W(x,t) + \sum_{x \in I_s} PV(x,t) \right] - L(t) \tag{1}
\]

where \( W(x,t) \) and \( PV(x,t) \) are respectively the normalized wind and solar hourly power output at site label \( x \) and date \( t \). The subsets \( I_w \) and \( I_s \) respectively list the spatial references of all installed wind and solar modules present in the system: \( I_w = \{ x_n \in I_{k,R} \mid \text{type}_n = \text{wind} \} \), \( I_s = \{ x_n \in I_{k,R} \mid \text{type}_n = \text{pv} \} \).

Let us point out that the hourly power mismatch can be either positive (\( \Delta_t > 0 \)) in which case there is an excess VREs production, or negative (\( \Delta_t < 0 \)) in which case production must be complemented to cover the demand. Obviously \( \Delta_t = 0 \) corresponds to an exact match between the hourly VREs supply and consumers needs.

Two different balancing mechanisms will be considered. First in the merit order, the system will relay on a generic and centralized round-trip storage technology. This storage is sized by definition of both its maximal stored energy capacity \( C_s \) and its charge-discharge rated power \( \zeta \). Furthermore it will be exclusively charged by excess VREs generation and will deliver energy to consumers whenever needed, within operational constraints. Energy conversion losses are accounted for by storage efficiency parameters \( \eta_{in} \) and \( \eta_{out} \) which in practice depend on the physical characteristics of the storage technology employed. To stay general we assume here an intermediate efficiency value \( \eta_{in} = \eta_{out} = 0.8 \) and no leaking. In case storage is unable to cover the mismatch the system will relay on a second balancing mechanism provided by fast ramping BPP. We will assume at first unlimited access to backup power capacity but optimal sizing will come along with our results. In practice the BPP capacity should be correctly sized to avoid blackouts on one side but also to limit costly over-capacity on the other side.

As the \( \zeta \) rated power acts like a limiting factor of hourly transaction between the storage facility and the network power flow we introduce a modified hourly power mismatch \( \tilde{\Delta}_t \) which specifies the storage aptitude to handle hourly mismatches:

\[
\tilde{\Delta}_t = \max \left( \min (\Delta_t, \zeta), 0 \right) + \min \left( \max (\Delta_t - \zeta, 0), 0 \right). \tag{2}
\]

Generally speaking optimal storage dispatch strategy is a complex task [15]– [30]. We assume here a straightforward policy where any excess VREs generation is stored unless storage is full and deficits are first covered by stored energy unless storage is empty. All transactions are of course limited by the storage ramping constraints, capacity limits and conversion losses. Thus the storage filling level time series \( S_t \) is given by

\[
S_t = \begin{cases} 
\min (S_{t-1} + \eta_{in} \Delta_t, C_s), & \text{if } \Delta_t \geq 0 \\
\max (S_{t-1} + \frac{1}{\eta_{out}} \Delta_t, 0), & \text{if } \Delta_t < 0. \end{cases} \tag{3}
\]

To avoid boundary value problems a one year spin-up period has been used to settle initial storage level \( S_0 \).

The time dependent storage power flow \( F_t \) is then given by \( F_t = S_t - S_{t-1} \) from which we can finally derive the additional backup contribution \( B_t \) such that

\[
B_t = \begin{cases} 
0, & \text{if } \Delta_t \geq 0 \\
\Delta_t - \eta_{out} F_t, & \text{if } \Delta_t < 0 \end{cases} \tag{4}
\]

where we have chosen to express backup energy in negative values for better clarity.

To summarize the simulation set up we start with a parameterized power system \( (P_{ren}, R, C_s, \zeta) \). The renewable power
$P_{\text{ren}}$ is evenly divided into $k \in \mathbb{N}$ units which are spatially distributed within the territory bounded by the maximal transmission distance $R$. Given the spatial and technological distribution of all units we calculate the hourly power mismatch (2). Balancing needs are in priority covered by reported VREs energy via storage (3). Whenever demand cannot be covered by either direct or reported renewable electricity some backup power is dispatched to fulfill the gap by means of (4).

E. Evaluating Performances

One key metric that we are interested in is the total backup energy use $\Psi_{(T)}$ during the simulation period $T$,

$$\Psi_{(T)} := \sum_{t=1}^{T} |B_{t}|,$$  \hspace{1cm} (5)

from which we define the renewable fraction $\Omega_{(T)}$ as

$$\Omega_{(T)} := 1 - \frac{\Psi_{(T)}}{\sum_{t=1}^{T} L(t)}.$$  \hspace{1cm} (6)

The renewable fraction is a measure of overall adequacy between load and VREs generation. As such an optimal spatial distribution of VREs generators should tend to maximize this quantity. Another metric of interest is the total backup power which suggests that allowing more than 20 units brings only negligible benefits, as showed in Appendix A. This parameter that is evenly divided into $k \in \mathbb{N}$ units which are spatially distributed within the territory bounded by the maximal transmission distance $R$. Given the spatial and technological distribution of all units we calculate the hourly power mismatch (2). Balancing needs are in priority covered by reported VREs energy via storage (3). Whenever demand cannot be covered by either direct or reported renewable electricity some backup power is dispatched to fulfill the gap by means of (4).

F. Optimal Spatial Distribution of VREs Units

Given a parameterized power system sizing ($P_{\text{ren}}, R, C_s, \zeta$) we use a heuristic genetic algorithm (GA) process in order to find near optimal spatial distribution of VREs units. We will only present here a quick overview of the algorithmic design, a more detailed description on evolutionary algorithms is given e.g. by Goldberg [31].

GA is a search heuristics inspired by natural selection theory and as such is traditionally described using biological analogies. An individual is a candidate solution to the optimization problem and is defined by his genotype, i.e., the set $I_{k,R} = \{(x_1, \text{type}_1), (x_2, \text{type}_2), \ldots, (x_k, \text{type}_k)\}$ which describes a specific $k$-units deployment over $\chi_R$. The collection of all possible distinct individuals corresponds to the configuration space. A generation is a subset of $n \geq 2$ individuals that are not necessarily all distinct. The basic principle of a GA is to perform selection, crossover and mutation operators on individuals of a parent generation $G_j$ to form (breed) a child generation $G_{j+1}$ with hopefully better performance regarding some fitness criterion. The newly born generation becomes then the parent generation at next iteration, the process being repeated until satisfaction is reached.

Within our setup, each of the $n$ distribution candidates of generation $G_j$ are first evaluated by running a complete simulation of hourly power balance (c.f. Section III-D) to obtain for each one of them an adaptation score from (6). Fitness proportionate selection is then used to form next generation: every offspring’s of generation $G_{j+1}$ will inherit parts of two parents genotype, where parents are selected with a probability proportional to their level of fitness. For instance, considering renewable fraction maximization, a parent with label $p \in \{1, \ldots, n\}$ is selected with probability $H_p$ such that

$$H_p = \frac{1}{\Psi_p \sum_{i=1}^{n} \frac{1}{\Psi_i}}.$$  \hspace{1cm} (8)

A crossover operator is then applied to shuffle genes between the selected parents. To avoid local extremum convergence the next step is to introduce a random exploration of search space using a mutation operator which will replace genes of the offspring’s with some given probability. Precisely, a new unit $(x_{i}, \text{type}_{i})$ within the candidate solution genotype is moved to a random location $x_{i} \in \chi_R$ and is randomly set to either PV or wind technology. By successive iterations the process should attain an optimally distributed pattern, respective to power system sizing ($P_{\text{ren}}, R, C_s, \zeta$) and objective function choice. In the context of this study the optimization process has been conducted to maximize the renewable fraction (6) for a wide range of power system parameters that are summarized in Table I, Appendix B. Note that, in order to ensure good convergence and limit computational cost, some refinements were used regarding mutation, crossover and seeding procedure. In particular an alternative greedy approach has been used to build up the heuristic. For the interested readers a more detailed description of the algorithmic process and associated aspects are presented in Appendices A and B. Selected values for our GA parameters are also given in Tables III and IV.

IV. RESULTS AND DISCUSSIONS

For our experimental results we will concentrate on two classes of scenarios. The first class of scenario restricts to power systems without storage capacity, where integration schemes rely only on spatial distribution patterns. In the second class of scenarios we introduce a generic storage which allow time domain transfer of load. The motivation behind this is to shed light on possible time domain transfer of load. The motivation behind this is to shed light on possible trade-offs between storage and grid strategies. To clarify scales we will express the installed renewable power $P_{\text{ren}}$ in terms of fraction of peak load (f.p.l.). Overall, spatial distribution of VREs units that maximizes renewable penetration has been determined for each one of 240 different scenarios (see Table I for parameters values). For all optimizations the number of VREs units has been set to $k = 20$. In principle results should be sensible to the value of $k$ as it fixes the degree of freedom for exploiting spatial complementarity. Sensibility tests were conducted which suggest that allowing more than 20 units brings only negligible benefits, as showed in Appendix A. This
remarkably indicates that optimal solutions tend to concentrate generation on few distinct sites regardless of power system sizing.

### A. No-storage Scenarios

We first investigate the share of electricity demand that can be met without storage capacity as a function of the aggregated VREs power $P_{\text{ren}}$ and accessible spatial extent $R$. As shown in Fig. 3 (a) renewable fraction $\Omega$ is strongly related to the grid extent although $R = 900$ km is marking a cutoff between two distinct regimes. This separation is also apparent in Fig. 3 (b) which presents the minimal backup sizing $\beta$ reached for the same optimal solutions. It appears that for $R > 900$ km and $P_{\text{ren}} > 0.6$, $\beta$ is linearly decreasing while solutions with $R \leq 900$ km always need a reserve capacity equivalent to the peak load.

To better understand this behavior results of Fig. 3 should be put in perspective with the solar-wind mix of solutions presented in Fig. 4 where $\alpha_w := \frac{(\text{number of wind units})}{k}$, thus $\alpha_w = 1$ is a wind only solution while $\alpha_w = 0$ is a PV only solution. It is noticeable that large scale optimal solutions are wind dominated in contrary to small scale solutions which are PV dominated. In both cases technology is unmixed when $P_{\text{ren}}$ is up to 75% of peak load and tend to mitigate beyond.

A general statement is that PV is better suited than wind energy for small grid integration but then the day night and seasonal cycles of solar resource also imposes important constraints on achievable penetration levels as well as needed reserve. Large grid VREs integration gives access to high potential wind sites which increases substantially the overall performances. Notably, for an installed renewable power equivalent to peak load, there is almost a 50% increase in renewable fraction of load while minimal backup power is

Fig. 3. (a) Renewable fraction $\Omega$ and (b) Backup minimal sizing $\beta$ as a function of $P_{\text{ren}}$ for different grid extents and without storage. Each value corresponds to optimally distributed generators, respective to the power system sizing scenario, and such that $\Omega$ is maximal. Different curves corresponds to different grid extents.

Fig. 4. Solar-wind mix of 120 optimal solutions as a function of spatial extent $R$ and $P_{\text{ren}}$. $R < 900$ km scenarios are dominated by PV technology while larger scale scenarios are dominated by wind. The mixing ratio starts to mitigate when $P_{\text{ren}} > 0.75$. 
Fig. 5. (a) Renewable fraction $\Omega$ and (b) backup minimal sizing $\beta$ as a function of $P_{ren}$ for different grid extents and with storage sizing $\zeta = 5 \text{ GW}$, $C_s = 3000 \text{ GWh}$. When compared with no-storage solutions presented in Fig. 3, mostly significant is the steep inflexion in backup sizing for $R > 600$ km.

reduced by about $10\%$ when grid domain is extended from $150$ km to $2100$ km. Performance results on the no-storage class of scenarios establish an important reference point on how VREs integration is affected by the definition of grid extent. In Section IV-C we will look into the spatial distribution patterns of optimal solutions but first we investigate the effect of adding storage into the system.

B. Storage Scenarios

We concentrate in this section on a single class of storage scenarios where $C_s = 3000 \text{ GWh}$ and $\zeta = 5 \text{ GW}$. This storage sizing is rather large as it corresponds to roughly 18 days of average load in terms of energy quantity and about half peak load in terms of power. While $\zeta = 5 \text{ GW}$ is comparable to the projected Swiss hydro pumped-storage power capacity at horizon 2025 [8] the chosen value of $C_s$ is one order of magnitude above projected pumped-storage reservoirs capacity (200 GWh) but is more in tune with the scales of this study.

The main reason to consider such a large storage is to provide an upper bound on storage strategies and gain better visibility on underlying dynamics as the most adapted capacity can be deduced ex-post for each distinct scenario if storage has not been saturated.

Results presented in Fig. 3 can be compared to their counterpart of Fig. 5 where values are again obtained from spatial distribution that maximizes renewable penetration but this time with the use of storage capacity.

As expected the renewable fraction is increased proportionally to $P_{ren}$ but at smaller grid extent integration still hardly exceeds $50\%$ and backup sizing is unaffected. Again PV based generation exhibits here strong constraints which cannot be overcome even by adding an important storage capacity. At larger grid extent an inflexion point occurs around $P_{ren}=100\%$ marking a steep decrease in backup sizing. A careful look at Fig. 5 suggests that backup sizing is strongly relaxed when $P_{ren}$ reaches about $85\%$ of peak load. Without storage the backup sizing decrease stays linear even above this threshold. In order to further investigate the interplay between storage (i.e., time) and grid (i.e., space) integration strategies Fig. 6 presents a monotonic representation of power mismatch and backup needs for selected scenarios. We compare here no-storage optimal solutions with their storage inclusive counterpart. Continuous lines describe the decreasing values of power mismatches (1) where points above the zero line stand for excess VREs generation. The dashed line corresponds to the increasing backup power infeed in presence of storage while the no-storage backup curve is by definition merged to negative values of no-storage power mismatches and zero otherwise. The first thing to mention is that the total energy delivered via storage corresponds to the area enclosed by the storage power mismatch curve and the dashed

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2 Projected Swiss pumped-storage needs are related to domestic VREs generation at penetration level of about $20\%$ while cumulated reservoir capacity of Swiss hydro-power plants is presently about 8700 GWh.
backup curve. Another important aspect is that different power mismatch shapes imply different spatial configurations of VREs units.

Looking at Figs. 6(b) and 6(d) we can see that the introduction of storage is accompanied by a redistribution of units which reinforces excess VREs generation but also reinforces negative mismatches. This is however not the case in Figs. 6(a) and 6(c) where both mismatch curves are nearly identical. While storage use is clearly growing with grid extent it appears that the interplay between spatial distribution and storage holds some subtleties. It seems logical that the possibility of time domain transfer will relax constraints on direct supply-demand equilibrium in presence of excess VREs generation and should thus favor spatial concentration, on the other hand growing renewable power and larger grids will widen spatial complementarity options. In order to clarify how this trade-off takes place we will continue our investigation by further looking at unit distribution patterns.

C. Spatial Distribution of Solutions

As a first insight, and to illustrate the pattern evolution of optimal solutions, Fig. 7 shows the geographical distribution of VREs units obtained for selected scenarios with \( R \) identically set to 1500 km and no-storage but varying values of \( P_{\text{ren}} \). Generally speaking solutions are highly concentrated at low VREs power and tend to spread progressively as installed renewable capacity builds up. A straightforward interpretation is that as long as excess VREs generation is low the optimization process favors quantity by selecting the most productive cell, but comes a point when it becomes beneficial to combine distinct generation profiles even if it lessens overall output. It is striking that, when spreading out, units still tend to cluster around several poles. This suggests that optimal distribution converges toward a specific interregional coupling, however it would be inappropriate to draw conclusions on a single example. Indeed, each set of parameters \((P_{\text{ren}}, R, C_s, \zeta)\) can correspond to a quite distinct configuration of units. To construct a broader representation we introduce a dispersion metric \( \delta_R \) such that for any \( R > 0 \) and for a given set of spatially distributed units \( \{x_1, \ldots, x_k\} \in \chi_R \)

\[
\delta_R := \frac{\sum_{i<j\leq k} d_h(x_i, x_j)}{\max \left( \sum_{p<q\leq k} d_h(x_p, x_q) \right)}
\]

where \( d_h(x_i, x_j) \) represents the spherical surface geodesic distance (haversine method) between units \( x_i \) and \( x_j \), \( \delta_R \) is thus constructed to take values between 0, when all units are concentrated on a same cell, to 1 when units are maximally spread. As a visual reference spatial distribution from Fig. 7(b) corresponds to \( \delta_R = 0.41 \) while Fig. 7(c) corresponds to \( \delta_R = 0.49 \). Calculated dispersion values for all scenarios, both with and without storage, are presented in Fig. 8.

For all grid extent spatial distribution (quasi-)monotonically evolves from perfectly concentrated to spread out configurations. This is obviously in agreement with our initial intuition, less obvious is the fact that all curves exhibit similar path and
Fig. 7. Distribution map for selected scenarios with $R=1500$ km, $k=20$ units and no storage. This Figure illustrates the evolution of optimal VREs units distribution from highly concentrated to widely spread out solutions. Notice however that when spreading out units still aggregate around several (coastal) distinct poles.

Fig. 8. Dispersion $\delta_R$ as a function of $P_{ren}$ for different grid extents. Without storage (a) and with storage (b). For all grid extents there is a minimum power threshold from which dispersion starts to monotonically increase. The introduction of storage does not significantly change dispersion values although there is globally a right side drift.

all tend to accumulate around $\delta_R=0.7$. Recall that technological repartition is quite different between spatial scales. As a matter of fact solar resource is much more spatially coherent than wind, it is thus a bit surprising to find such similarities. It appears also that the introduction of storage does not drastically change distribution. For some grid extent there is effectively a right side drift, e.g., in the inflexion point when full concentration of units relaxes but it is not true in general. Dispersion is even increased for some scenarios at higher renewable penetration. Another interesting aspect is that in both graphs the inflexion point is not directly proportional to the grid extent as one could have expected, in fact intermediate spatial domains are the first to hook off from $\delta_R=0$. (Table I, Appendix B)
V. Conclusion

Integration potential for a solar-wind based power system has been investigated using an optimal distribution search algorithm, in combination with a parametric physical simulation of hourly power mismatches. A motivation for this research was to illuminate options and constraints on the transitional path towards a fully renewable power system, taking a central European perspective. In this respect our results show a strong incentive to expand the spatial distribution of renewable units as small scale deployment greatly limits what is achievable in terms of penetration level. This is however without considering decisive economic factors such as needed transmission investments or market design, which surely are aspects that have to be accounted for. Our findings that increasing spatial extension plays a strong role for VREs integration is also in good general concordance with previous studies, such as in [3], [5], [6], although direct comparison is made uneasy because of the difference in representation.

A main contribution of this study is to explicitly define best possible geographical distribution of VREs generators for growing power system sizing. As such it provides an upper bound on integration schemes useful for framing the ongoing energy transition debate. Implemented in a more detailed power system simulation this modeling approach could be part of a decision-making tool for electricity planners, allowing to identify advantageous system design.

Considering ambitious renewable targets our results reveal possible forthcoming systemic bottleneck. From the central European standpoint grid extension is already critical to achieve efficiently a 30% VREs penetration target, and becomes absolutely necessary for penetration levels above 50%. Accessing high capacity factors of particularly windy locations appears to be one main reason, but large scale grid enables also to connect widely spread hot spots that nicely complement each other.

Introduction of storage also appears to be mostly beneficial when associated to large scale distribution as it enables a significant decrease in backup power sizing, on the contrary to small grid integration, although the overall smoothing effect of storage only occurs at a fairly high share of VREs power. Optimal distribution of units is also subject to variations when storage is added, allowing more quantity oriented configurations, but there is in any case a threshold point from which unit dispersion starts to improve performances. A key finding is that dispersion however does not increase steadily toward a fully atomized geographical dispersion but settles on multipole arrangements, independently of grid extent. One aspect that our study does not clarify is how narrow the distribution optimums are. This should be further investigated.

Swiss hydro-power dynamics has not been directly integrated in our methodological setup in order to get a general sense of interacting strategies focused on VREs. Let’s mention that the model responses should be weakly sensitive to the introduction of some baseload capacity, as far as peak load is redefined as the maximal power gap between load and baseload generation. However hydroelectricity entails its own variability, mainly seasonal, that will somehow affect optimality of solutions. This aspect along with a more advanced representation of storage scheduling is setting ground for further research prospects, notably in the context of forecast uncertainties.

Our case study findings may also not generalize to other load centers, notably for coastal locations that have near access to high wind profiles. Nevertheless for most central European locations we can expect to find similar characteristics. It would be interesting to carry out this same analysis on different regions and at higher spatial resolution to further enhance the general understanding of underlying dynamics.

Increasing transactions between European load centers indicates that the power system is already heading towards an extended network [7] although the ideal transmission grid design is still under question. Focusing on a wind and solar based power system we have identified some inherent physical limitations and opportunities, framing the range of possible tempo-spatial integration options from a localized perspective. Yet a number of other alternative options and synergies can be locally exploited to fully realize the ongoing energy transition. Among them demand-response strategies are of particular interest in the context of highly renewable but locally flexible power systems. Adding demand side flexibility would be a consistent next step to this study.

Acknowledgments

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Appendix A

Optimal Distribution Search Algorithm

Given the setup introduced in Section III our objective is to find the best geographical distribution of $k \in \mathbb{N}$ VREs units of power $P_{\text{ref}} = P_{\text{ren}}/k$, such that $\Psi (5)$ is minimal while subject to the parametrized power system sizing $(P_{\text{ren}}, R, C_z)$. The set of accessible siting locations is denoted by $\chi_R = \{ x \in N \mid d_T(\{x, x_0\} \leq R \}$ (Section III-A) with cardinality $|\chi_R| = \text{card}(\chi_R)$. There is no restrictions on the number of units a given site can host. For fixed values of $k$ and $R$ the size of the configuration space of the system is thus:

$$S(|\chi_R|, k) = \frac{(2|\chi_R| + k - 1)!}{k!(2|\chi_R| - 1)!}$$ (10)

Although values for $|\chi_R|$ are exogenously determined by the spatial resolution of the study we have some liberty regarding values for $k$. This is an important choice because it fixes the degrees of freedom for spatial repartition of VREs capacity. On the other hand, looking at (10), we can see that it will have a significant impact on the computational cost of the optimization process (Table II). As we had no a priori knowledge on the optimal distribution of units we made some empirical testings on selected parameter sets in order to better determine the best value for $k$. In essence it consisted in running GA optimization procedures with increasing number of units while adapting the iteration depth. To help convergence successive “$k$-runs” where seeded with...
the best distribution solution found at the previous run (that is when \( k \) was smaller). A sample of results obtained doing so is presented in Fig. 9. We found that the fitness of solutions was only marginally improved when exceeding 20 units. We should stress out that, as indicated by our experimental results from Section IV-C, there is a power limit before which optimality is attained through spatial concentration. For those parameter sets best solutions are quantity oriented and the number of units is in fact irrelevant. Knowing this it is possible to alleviate computational cost by lowering the number of units for smaller VREs power sizings, although we did not do so in this present work for methodological consistency. It is also worth mentioning that an alternative greedy procedure, which will be explained shortly after, has been used to double check our sensibility analysis over \( k \) which is why we have chosen to use a dynamic mutation rate and two alternative crossover procedure. Finally, the initial generation is partially seeded with the greedy solution as well as an “elite” choice, and so forth until the last best \((x_k, \text{type}_k)\) is reached. Computationally this represents \( 2k|\chi_R| \) simulation iterations which is by far lesser than for standard GA optimizations although the greedy approach does not (neither) guarantee to reach a global optimum. In fact depending on sizing setups the GA was able to outperform greedy solutions which justifies its use (see Fig. 10 for an illustration). This said the greedy approach has however good practical interest and is used as a seeding procedure in our GA design as well as to help calibrate the evolutionary operators.

![Fig. 9. Relative fitness as a function of number of units \( k \) for selected scenarios.](image)

An alternative to the GA is to adopt a greedy approach on the problem. Given \( k \) and \( R \) we denote a particular VREs deployment by: \( I_X = \{(x_1, \text{type}_1), (x_2, \text{type}_2), \ldots, (x_k, \text{type}_k) \mid x_i \in \chi_R, \text{type}_i \in \{pW, \text{wind}\} \} \), where the \( \lambda \) index is running through the configuration space \( \lambda = 1, 2, \ldots, S(|\chi_R|, k) \). The idea is then to first iterate over \( |\chi_R| \) a single unit simulation in order to determine the best \((x_1, \text{type}_1)\) choice. Fixing this single unit optimum we proceed by finding the best \((x_2, \text{type}_2)\) choice, and so forth until the last best \((x_k, \text{type}_k)\) is reached.

![Fig. 10. Greedy solutions versus GA solutions as a function of \( P_{\text{gen}} \).](image)

We now proceed to present in more details the GA we have designed for this research, the generic procedure is presented in Appendix C. Specific values used for GA parameters, such as generation size and operator rates, are presented in Table VI. We recall that the relative fitness of a candidate solution \( I_p \) is \( H(I_p) = \left( \Psi_p \sum_{i=1}^{n} \frac{1}{\Psi_{I_i}} \right)^{-1} \), where \( \Psi_{I_i} \) is calculated with the simulation model presented in Section III-D. As the size of the search space is directly related to the spatial extent parameter \( R \) the iteration depth is set in proportion (Table III). Also, depending on the parametric sizing of the system strong candidates can be either highly concentrated units or widely distributed. In other words it is important to try to equilibrate the heuristic to manage a diversity of possible outcome. This is why we have chosen to use a dynamic mutation rate and two alternative crossover procedure. Finally, the initial generation is partially seeded with the greedy solution as well as an “elite” selection of VREs units, the rest being randomly taken.

### Appendix B

**TABLE I**

**POWER SYSTEM PARAMETRIC SIZING. EACH 240 COMBINATIONS OF THE PARAMETERS CORRESPOND TO A DISTINCT SCENARIO THAT HAVE BEEN SEPARATELY OPTIMIZED.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Units</th>
<th>Tested values</th>
</tr>
</thead>
<tbody>
<tr>
<td>( P_{\text{gen}} )</td>
<td>f.p.l.</td>
<td>0.15, -0.3, -0.45, -0.6, -0.75, -0.9, -1.05, -1.2, -1.35, -1.5, -1.65, -1.8, -1.95, -2.1, -2.3</td>
</tr>
<tr>
<td>( R )</td>
<td>km</td>
<td>CH(150), -300, -600, -900, -1200, -1500, -1800, -2100</td>
</tr>
<tr>
<td>( C_p )</td>
<td>GWh</td>
<td>0, -3000</td>
</tr>
<tr>
<td>( \zeta )</td>
<td>GW</td>
<td>0, -5</td>
</tr>
</tbody>
</table>

**TABLE II**

**CONFIGURATION SPACE SIZE RELATIVE TO GRID EXTENT DOMAIN FOR \( k = 20 \).**

<table>
<thead>
<tr>
<th>( R ) (km)</th>
<th>CH</th>
<th>300</th>
<th>600</th>
<th>900</th>
<th>1200</th>
<th>1500</th>
<th>1800</th>
<th>2100</th>
</tr>
</thead>
<tbody>
<tr>
<td>(</td>
<td>\chi_R</td>
<td>)</td>
<td>14</td>
<td>33</td>
<td>119</td>
<td>267</td>
<td>446</td>
<td>638</td>
</tr>
<tr>
<td>( S(</td>
<td>\chi_R</td>
<td>, 20) )</td>
<td>( 10^{13} )</td>
<td>( 10^{19} )</td>
<td>( 3 \cdot 10^{29} )</td>
<td>( 2 \cdot 10^{46} )</td>
<td>( 5 \cdot 10^{46} )</td>
<td>( 5 \cdot 10^{46} )</td>
</tr>
</tbody>
</table>

**TABLE III**

**ITERATION DEPTH AS A FUNCTION OF SPATIAL EXTENT.**

<table>
<thead>
<tr>
<th>( R ) (km)</th>
<th>CH</th>
<th>300</th>
<th>600</th>
<th>900</th>
<th>1200</th>
<th>1500</th>
<th>1800</th>
<th>2100</th>
</tr>
</thead>
<tbody>
<tr>
<td>( T(R) )</td>
<td>600</td>
<td>800</td>
<td>1000</td>
<td>1500</td>
<td>2000</td>
<td>2500</td>
<td>3000</td>
<td>3500</td>
</tr>
</tbody>
</table>
### TABLE IV

<table>
<thead>
<tr>
<th>$k$</th>
<th>$n$</th>
<th>$n_1$</th>
<th>$n_2$</th>
<th>$Mr$</th>
<th>$Cr$</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>55</td>
<td>6</td>
<td>6</td>
<td>0.1</td>
<td>0.4</td>
</tr>
</tbody>
</table>

### APPENDIX C

**Algorithm 1 Optimal Distribution Search Algorithm**

**Given:**

$(P_{\text{st}}, R, C_s, \zeta)$ – The parametric sizing of the power system.

$n$ – The number of individuals in each generation ($n > 1$).

$X_R$ – The set of accessible cells for VREs units.

$k$ – The number of VREs units, i.e. the number of genes in each individual chromosome.

$F(\cdot)$ – The fitness criterion on which individuals will be evaluated.

$Mr$ – The nominal mutation rate.

$Cr$ – The nominal crossover rate.

$T(R)$ – The number of generations (function of $R$).

**DO:**

1. Initial seeding procedure:
   1.1 Calculate the greedy solution $I_g$.
   1.2 Calculate an elite solution $I_c$ over $X_R$ by selecting the $k$ fittest single individuals.

2. Populate initial generation $G_0$ of $n$ individuals $G_0 \leftarrow \{I_{p_1}, \ldots, I_{p_n}\}$:
   
   for $j \leftarrow 1$ to $n_1$
   
   populate initial generation with greedy solution: $I_{p_j} \leftarrow I_g$.
   
   for $j \leftarrow n_1 + 1$ to $n_2$
   
   populate initial generation with elite solution: $I_{p_j} \leftarrow I_c$.
   
   for $j \leftarrow n_2 + 1$ to $n$
   
   populate initial generation with random individuals $I_{p_j} \leftarrow \text{random}$.

3. Evaluate fitness criterion $F(I_{p_j})$ of each individual in $G_i$ with simulation model.

4. Rank individuals according to fitness.

5. Re-construct most fit member in child generation: $I_{c1} \leftarrow \text{most fit } I_{p_j}$.

6. Calculate the diversity factor of current generation: $df \leftarrow \text{number of unique } I_{p_j}/n$.

7. Adapt the mutation rate: $mr \leftarrow Mr \leftarrow \left(\frac{3n(df-1)}{1+2n}\right)$.

8. Selection and Crossover:
   
   for $j \leftarrow 2$ to $n$ (by 2) do:
   
   Select two parents $\{I_{p_A}, I_{p_B}\}$ in $G_i$ with probability proportional to fitness.
   
   if (rank $I_{p_A} + \text{rank } I_{p_B} < 0$):
   
   One-point crossover between parents.
   
   else for $j \leftarrow 1$ to $k$
   
   With probability ($C_y$): swap parents $j$th genes.
   
   Assign result offspring’s child generation: $I_{c_j} \leftarrow I_{p_A}$ and $I_{c_{j+1}} \leftarrow I_{p_B}$.

9. Mutation:
   
   for $j \leftarrow 1$ to $n$
   
   for $g \leftarrow 1$ to $k$
   
   With probability ($mr$): Replace gene number $g$ in $I_{c_j}$ chromosome with a random gene.

10. Add current generation to population.

11. Create new generation: $G_{i+1} \leftarrow I_{c1}, \ldots, I_{cn}$.

**End While**

12. Return (Most fit member of population).

**End DO**

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