An Evolutionary Approach to Geo-Planning of Renewable Energies

Daniel Lückehe[1], Oliver Kramer[2], Manfred Weisensee[3]

Abstract

Renewable energy sources are getting more and more important in many industrial nations. As their behavior and effectiveness often depends on their location, the employment of geo-planning and geo-optimization strategies improves their value. A geo-planning process must consider multiple aspects and different requirements resulting in a constrained optimization problem. In this work, we introduce a new optimization approach for geo-planning based on evolutionary strategies. For this sake, we adapt evolutionary operators and employ deterministic parameter control. We define an experimental setting for wind turbines with different potentials, constraints, and wake effects. In the experimental part of this work, we first show the behavior of the approach on toy settings. Extended settings with real-world geographical data, ground mounted solar power plants, and political conditions demonstrate the flexibility and extensibility of the approach.

1. Introduction

While many European countries increase their renewable energy resources, the requirements for geo-planning are becoming more and more complex. Old fossil power plants are replaced by smaller regenerative energy sources, whose behavior and effectiveness depend on their location. It becomes necessary to analyze and plan the participants in energy systems, e.g., strategies for generators, consumers, and storages in a smart way [1]. In order to reduce the load of power grids and to optimize output from regenerative energy sources, geo-planning has an important part to play. In particular, the increasing number of renewable energy sources leads to the requirement of their careful integration into the environment [8]. Therefore, many different parameters, which affect power output, have to be considered, e.g., wind potential for a wind turbine, wake effects, statutory frameworks, the development of an existing power grid, and the locations of consumers. The fast expansion of renewable energy sources is not the primary target. The German Federal Ministry for the Environment defined the objective to treat all participants of the energy system in an optimized and integrated way [4].

The objective of this work is to introduce a new optimization approach for geo-planning. Our approach should be able find optimal locations for various types of power plants. Therefore, the approach takes into account different criteria, e.g., environmental constraints, constraints between power plants, and varying power potentials at different locations. This work shows that evolutionary strategies (ES) can be a good approach for geo-planning that is able to consider different objectives.

This paper is structured as follows. In Section 2, we will give a general introduction to ES. Our geo-planning model will be illustrated in Section 3. In Section 4, an experimental analysis will show the capabilities of our approach. Conclusions are drawn in Section 5.

[1] Jade University of Applied Sciences, Oldenburg, Germany, daniel.lueckehe@uni-oldenburg.de, Department of Geoinformation

[2] University of Oldenburg, Oldenburg, Germany, oliver.kramer@uni-oldenburg.de, Department of Computing Science

[3] Jade University of Applied Sciences, Oldenburg, Germany, weisensee@jade-hs.de, Department of Geoinformation

2. Evolutionary Strategies

To find a location for new wind turbines, solutions can be evaluated w.r.t. different objectives, e.g., effects on the power grid or w.r.t. the wind potential. From this perspective, the problem becomes a multi-objective optimization problem. We call the function to evaluate solutions fitness function in the following. Which approach should be used to solve an optimization problem w.r.t. the fitness function depends on their characteristics. If the derivation of the fitness function is known, Newton-based methods like the Broyden-Fletcher-Goldfarb-Shanno algorithm are recommendable choices [11]. If the fitness function is non-differentiable or the computation of the derivation is too expensive, it is a good choice to treat the optimization problem as a black box. In black box optimization, no assumptions are made on the fitness function, allowing the employment of complex and combined fitness functions. For example, in a solution space that can be described by a simple fitness function like classic sphere function $f(x) = x^2$ the knowledge of mathematical description is a great advantage for finding the optimal solution. But the more complex the solution space is, the more difficult is a mathematical description and the search for an appropriate method to solve the equations. Treating the optimization problem as a black box problem has the advantage that the fitness function can have various characteristics, e.g., an equation, which models wind wake effects, the interpolation between discrete measurements of data or results of grid simulation programs. The ES is constructing a solution x_i, interprets the value of its fitness function $f(x_i)$, but does not require further knowledge of f. ES are a proven approach to solve black box optimization problems. They were developed independently in Germany by Rechenberg [13] and Schwefel [14] and in the United States by Holland [6]. Since their invention, ES were continuously further developed in various fields. Also in the field of wind turbine placement optimization, they are a highly modern method like shown by Tran et al. [15].

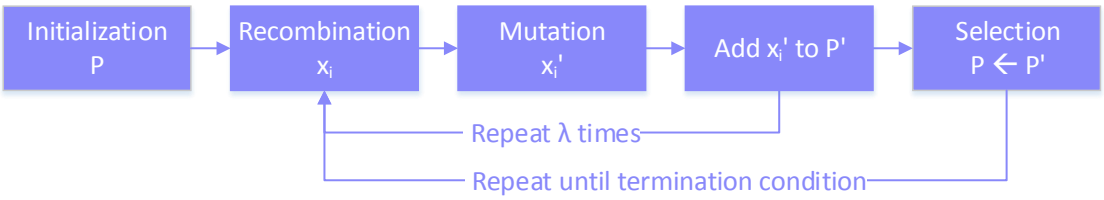

Figure 1: Evolutionary Strategy

Evolutionary strategies are inspired by the biological process of optimization, which is called evolution. The optimization process can be split into three main operators: recombination, mutation, and selection. Figure 1 visualizes the process of an ES. The first step is to initialize solutions $\{x_1, \dots, x_\mu\}$. These solutions are the initial population and will be called $\mathcal{P}$. Recombination will pick ρ solutions from $\mathcal{P}$ and create a new solution x_i by combining their parameters. There are numerous ways to accomplish this, e.g., for rational numbers the mean value can be calculated. The next step is to mutate solution x_i to x_i'. For rational numbers a common choice is Gaussian mutation where it applies $x_i' = x_i + \sigma \cdot \mathcal{N}(0,1)$ while $\mathcal{N}$ is the Gaussian distribution and σ is the step size. The mutated solution x_i' will be added to new population $\mathcal{P}'$. Recombination and mutation will be repeated λ times. So the size of new population is λ. Selection chooses the μ best solutions and replaces population $\mathcal{P}$ for the next generation. In a $(\mu + \lambda)$-ES, the best solutions can be chosen from $\mathcal{P}$ and $\mathcal{P}'$. In a (μ, λ)-ES, they can only be chosen from $\mathcal{P}'$. To rank the solutions, the fitness function $f(x_i)$ is used. For a maximization problem, for the best solution x^* it holds $f(x^*) \geq f(x)$ for every $x \in X$.

3. Geo-Planning Model

In this section, we introduce our evolutionary approach for geo-planning. First, the optimization problem is defined. For wind turbines, the turbine model, potential maps, constraints between turbines, and wake effects are specified. This setting is used in the experimental section for our wind turbine experiments. In the last paragraph the specification is extended to real world data from OpenStreetMap and simple models for solar power plants and political framework conditions. This extended setting shows the flexibility of the evolutionary approach when handling different objectives.

3.1. Evolutionary Approach

In our approach, we use a $(1+1)$-ES, i.e., the ES generates one offspring solution ($\lambda = 1$) in each generation and selects the better solution (offspring or parent, $\mu = 1$). A solution x_i contains multiple elements e and every element represents an energy source on a map in a defined location. In this work, we consider different types of energy sources, e.g., small and large wind turbines and solar power plants. For example, element $e_{wind(0,0,135)}$ represents a wind turbine placed at position $(0,0)$ with a turbine height of 135 meters. The solution, which only includes this wind turbine would be $x_i = [e_{wind(0,0,135)}]$. We define a solution that includes more than one energy source as $x_i = [x_{i1}, x_{i2}, x_{i3}]$ with the number of energy sources $N = 3$, e.g., $x_i = [e_{wind(0,0,135)}, e_{wind(2000,1000,78)}, e_{\mathrm{wind}(3000,3000,78)}]$. Then, it holds $x_{i0} = e_{wind(0,0,135)}$ and $pos\left(e_{wind(0,0,135)}\right) = (0,0)$. A solution is evaluated with the help of a fitness function. The objective is to maximize power potential P, which depends on position $pos\left(x_{ij}\right)$. The value of fitness function is the sum of every energy sources potential. It holds:

$$f(x_i) = \sum_{j=1}^{N} f(x_{ij}) = \sum_{j=1}^{N} P(pos(x_{ij})) \tag{1}$$

In case of the population-less $(1+1)$-ES, recombination does not apply. In our approach, mutation of solution x_i can add a new element e_{new} to solution x_i or change the position of an existing element e of solution x_i. The position for a new element e_{new} is chosen randomly anywhere in the defined area. For the change of a position Gaussian mutation is applied and the step size σ is adapted deterministically. It follows the principle of starting with a large step size, which covers the entire area, and ending with a very small step size to fine-tune the solution. When changing the position of an element, the ES can also change parameters from element e, e.g., the height of a wind turbine, with chance c. In the first generation, this chance is set to 50% and is reduced in the course of the optimization process. It holds:

$$\sigma(t) = 1.0 - \left(\left(1.0 - \frac{1}{T}\right) \cdot \frac{t}{T}\right) \text{ and } c(t) = 0.5 - 0.5 \cdot \frac{t}{T} \tag{2}$$

Where t is the actual number of generation and T is the total number of generations. At the beginning, the ES starts with an empty solution, which means initial population $\mathcal{P} = \{x_0\}$ with $x_0 = []$. In the geo-planning process, there are many constraints that have to be considered, e.g., laws and physical limits. In our approach, we employ a constraint handling method known as death penalty to enforce the fulfilment of constraints. That means every infeasible solution that has been created by mutation is discarded.

3.2. Wind Turbines Setting

The characteristics of the wind turbine E101 by Enercon is the basis of our approach. E101 is a very modern wind turbine. Further, we define that small turbines have a height of 78 meters, while large turbines have a height of 135 meters. The characteristics and power curves are taken from

Haack [5], Manwell et al. [10], and Gasch and Twele [3]. In real world data settings, interpolated data from the COSMO-EU model [2] are used for determination of the wind power potential $P(pos(x_{ij}))$. For every wind turbine, we define the constraint that no other turbine may be placed in an ellipse of a size that is five times the height of the turbine in the main wind direction and three times orthogonally to the main wind direction. In this work, the main wind direction is defined as coming from south west, which is a standard assumption for most places in Lower Saxony, Germany. The placement of a wind turbine affects the wind potential in the close neighborhood. These effect are called wake effects and are caused by complex physical principles. In our approach, we employ a simple wake model from Kusiak and Zong [9]. We modified the model focusing on the main wind direction of Lower Saxony with the simple model:

$$P_{wake}(\cdot) = \left(1.0 - \sqrt{\sum_j \left(\frac{1.0-\sqrt{1.0-c_T}}{1.0+\kappa\cdot(\cos(\alpha)\cdot\Delta x+\sin(\alpha)\cdot\Delta y)/R}\right)^2}\right)\cdot P(\cdot) \tag{3}$$

with $c_T = 0.8$ and $\kappa = 0.075$ as proposed by Kusiak and Zong. As we use the wind turbine Enercon E101 for wind, the rotor radius is set to $R = 55.5$. The angle α is the main wind direction and Δx, Δy are the differences between the target position and the positions of wind turbines e_j. The index list j contains indices of every element e of solution x_i, for which it holds $R + \kappa \cdot dist(\Delta x, \Delta y, \alpha) + bd(\Delta x, \Delta y, \alpha) > 0$ and $R + \kappa \cdot dist(\Delta x, \Delta y, \alpha) - bd(\Delta x, \Delta y, \alpha) > 0$ and $dist(\Delta x, \Delta y, \alpha) > 0$ with the distance $dist(\Delta x, \Delta y, \alpha) = \cos(\alpha) \cdot \Delta x + \sin(\alpha) \cdot \Delta y$ and border $bd(\Delta x, \Delta y, \alpha) = -\cos(\alpha) \cdot \Delta x + \sin(\alpha) \cdot \Delta y$.

3.3. Extended Setting

The experimental wind turbine setting will be extended in this section. We add geographical information from OpenStreetMap [12] and define restrictions for areas around buildings and streets. It is possible to define various restrictions for different regions, e.g., residential zones and industrial parks. In this setting, we define a global minimum distance of 150 meters between energy sources and streets implemented with rectangles, as well 300 meters from sources to buildings based on circles.

Ground mounted solar power plants have an economical minimum size of approximately 30,000 square meters [7]. To demonstrate the possibility to integrate new features into an existing solution, we first generate a solution for wind turbines. After the wind-based optimization process, the wind turbine placement method will be reused to search for solar power plant locations. In this process, positions are chosen randomly, similar to the process for wind turbines. The width constraint for solar plants is also chosen randomly, while the length is computed depending on the width w.r.t. an area of 30,000 square meters. An interesting aspect is the integration of new features into the optimization process. We employ political conditions to illustrate this possibility. Along technical factors, political aspects are playing an important role in a real-world decision making process. For example, if the numbers of wind turbines are equal in two communities, both are assigned to the same trade taxes. We define a function $n_{region}(x_i)$ that returns the number of elements in a region for a solution x_i. Political objectives can be modeled in the optimization process based on restriction $abs(n_{communityA}(x_i) - n_{communityB}(x_i))$, which must be smaller or equal to One.

4. Experimental Results

In this section, we experimentally analyze the proposed geo-planning approach based on the $(1+1)$-ES with various settings like described in Section 3.

4.1. Wind Turbine Experiments

The left part of Figure 2 shows an example of a wind potential map with four optima, i.e., a scenario with four mountains and strong wind. Violet and white areas reflect the magnitude of wind potential, while violet stands for low and white for high potential. In this case white areas are covered by the turbines. Black squares with a wind turbine icon symbolize the wind turbines and are labelled with W1 to W4. The ES fulfilled the constraint to place only four wind turbines with a height of 135 meters. In all 100 experimental runs, the $(1+1)$-ES was able to find the global optima. The $(1+1)$-ES was run for 10,000 generations taking less than one second on a usual home computer. On the right of Figure 2, the wind potential is equally distributed without wake effects. The ES places wind turbines in the solution space without numerical limitations. The figure demonstrates that every turbine constraint has been considered.

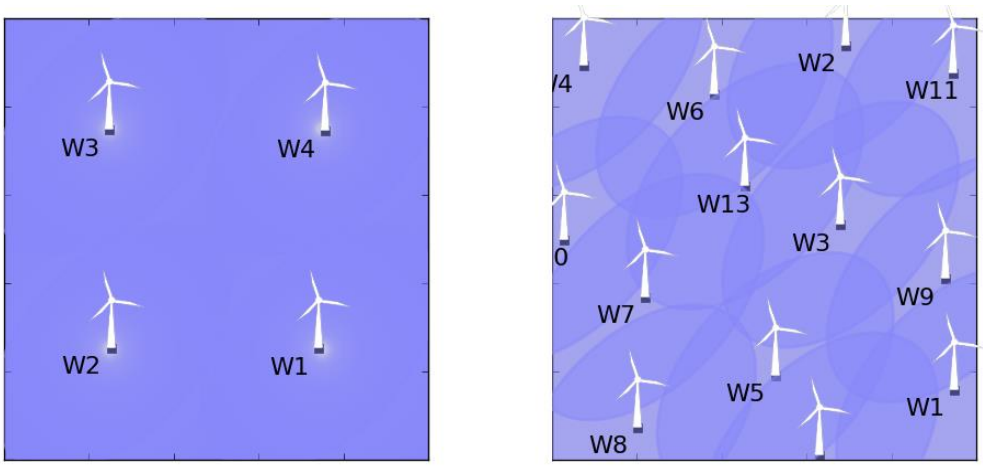

Figure 2: Left: potential map with four optima and four wind turbines, right: result of ES with many wind turbines

In the following experiment, wake effects are considered and visualized. Again, we are using a potential map with four optima. But in this case, the size of optima are increased. The ES can choose different positions within the optimal regions, which all belong to a global optimal solution. The optimum in the upper right corner has been increased to allow the placement of two wind turbines. As shown in the left part of Figure 3, the upper right optimum can be affected by wake effects.

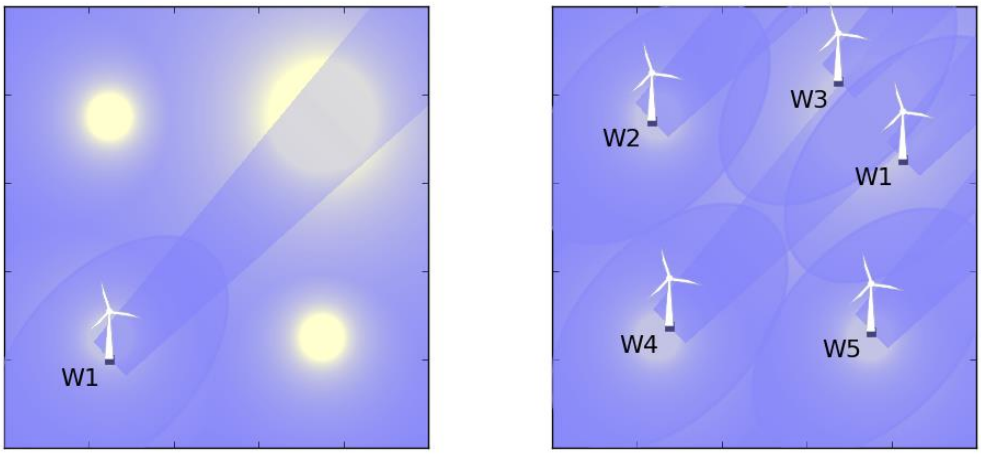

Figure 3: Left: one turbine with wake effects, right: five turbines with optimal solution

In this setting, the task is to place five turbines. The experiments show that the $(1+1)$-ES is able to find the optimal solution, which is depicted in the right part of Figure 3. Turbine W4 has been placed in the middle of the optimal region w.r.t. the perspective of the main wind direction. As a consequence, Turbines W1 and W3 can be placed in the optimal region without being affected by wake effects of W4. Turbines W2 and W5 are placed arbitrarily in the other optimal regions. Because of local optima situations, the $(1+1)$-ES was not able to find the global optimal solution in every test run. Preliminary experiments have shown that this issue can be solved by special mutation operators that will be subject to our future work.

In the last experiment for wind turbines, we are going to show the capability of $(1+1)$-ES dealing with turbines of different heights. Larger turbines have a higher power potential than smaller ones. Hence, an algorithm that optimizes the power potential will probably prefer larger turbines. In real world scenarios, small turbines are cheaper. Modelling financial aspects is possible, but not yet considered. For this reason, we define a power potential relative to costs in this scenario. In the left part of Figure 4, the relative potential prefers large turbines, while it prefers small turbines on the right hand side. In this experiment, the potential is at the same level on the map. On the diagonal, it is slightly higher. So it applied $P(\cdot) = 1.0 - abs(x-y)$ with $abs(x-y) \ll 1.0$. This is due the fact that in real world scenarios, the wind potential will also not be equal on the whole map.

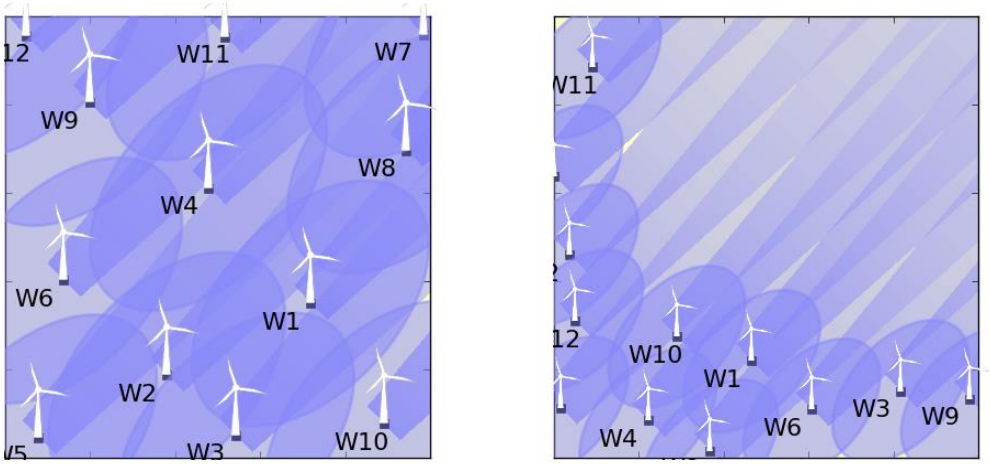

Figure 4: Left: placement of 12 large turbines, right: 12 small turbines

In the last experiment, the task is to place 12 turbines. With placing large turbines, see left part of Figure 4, some turbines have to be placed at locations that are affected by wake effects of other turbines. The $(1+1)$-ES minimizes these effects and places the wind turbines on the opposite side w.r.t. to the main wind direction. The turbines are also placed in lines orthogonally to the main wind direction. On the right hand side of Figure 4, a solution with many small wind turbines is shown. As smaller turbines can be placed closely together, it is possible to place all turbines without being affected by wake effects. The $(1+1)$-ES is able to find these solution, as shown in Figure 4. But again the search process can fail to find the global optimal solution due to local optima.

4.2. Extended Experiments

On the left hand side of Figure 5, two solar power plants are placed in a tiny real world setting. Like in all following plots with information from OpenStreetMap [12] yellow lines represent streets. Grey lines symbolize buildings. The constraints around streets and buildings are shown in red. The Figure illustrates that all constrains were considered. The regions for the solar power plants have been shaped to fit into the setting by the $(1+1)$-ES.

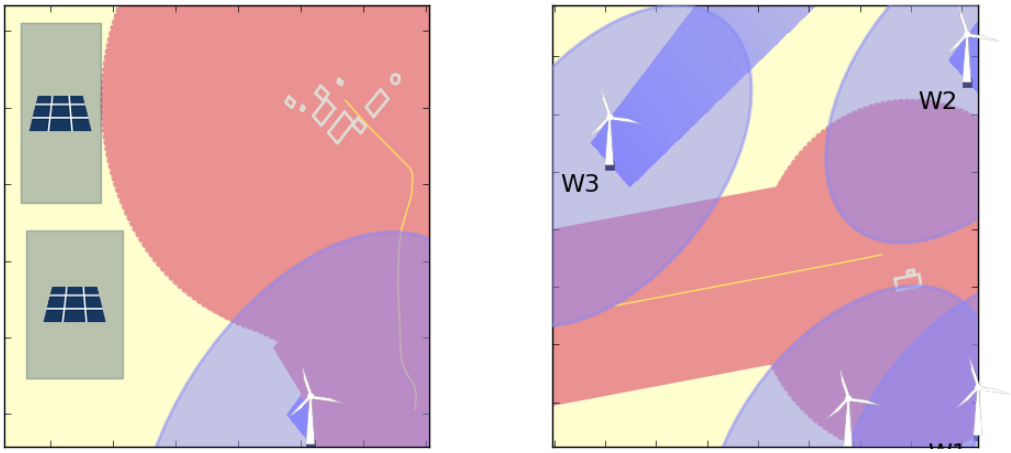

Figure 5: Left: placement of two solar power plants in a setting with buildings, streets, and a wind turbine, right: placement of four wind turbines, equally distributed above and below a street

On the right in Figure 5, the $(1 + 1)$-ES places four wind turbines with the political objective to place the turbines equally distributed above and below the street in this setting.

The last experiment is shown in Figure 6. In this setting, a village in Lower Saxony was chosen. It contains 139 buildings and 95 streets that consist of 454 parts. The computation of 50,000 generations takes less than thirty seconds on a usual home computer. The $(1 + 1)$-ES considers all constraints and places all wind turbines without being affected by wake effects, e.g., Turbine W5 is placed as close as possible to Turbine W3 without avoiding the minimum distance between turbines and being affected by wake effects. The gap between Turbines W1 and W2 has exactly the size of the wake effects of turbine W4 at location of W1 and W2.

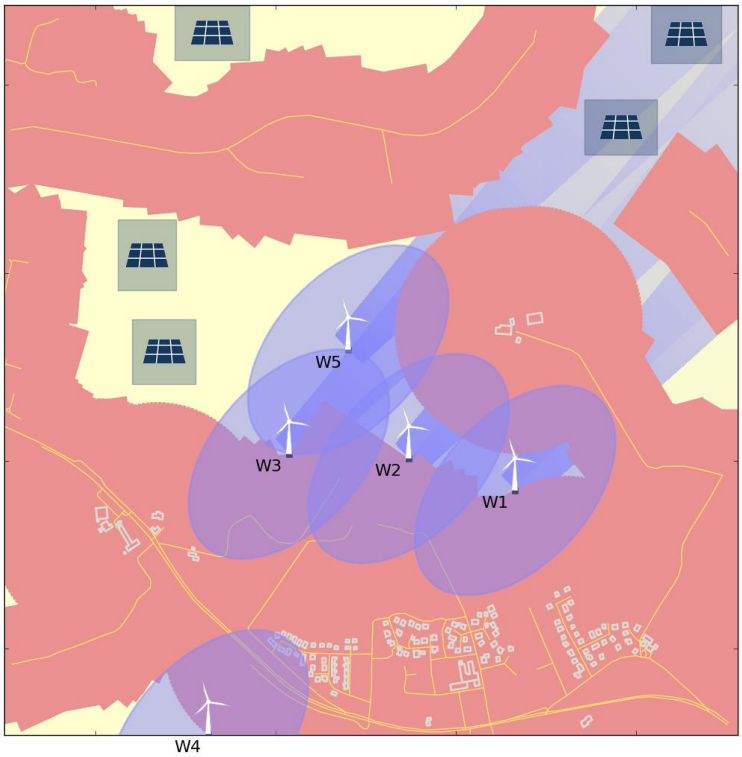

Figure 6: Five turbines and five solar power plains placed in a setting with a village

5. Conclusion

In our work, we have introduced an evolutionary approach for geo-planning that optimizes power potential and considers various kinds of constraints. We define a wind setting, where we use a turbine model based on a modern turbine, employ wind data from the COSMO-EU model, and add restrictions between turbines and wake effects. In our experiments, the $(1+1)$-ES considered all aspects and evolved valid solutions. Although the $(1+1)$-ES was demonstrated to find optimal solutions, there are still situations, when local optima can prevent finding the global optimum. In an extended setting, we employed geographical data from OpenStreetMap and also considered ground mounted solar power plants as well as political conditions. Again, the $(1+1)$-ES was able to handle all these aspects and demonstrated its flexibility.

In our future work, we will focus on leaving local optima with specialized mutation operators. Further, initial tests have shown promising results by optimizing multiple energy sources at once instead of only one. We also plan to add more features into the settings, e.g., more detailed solar power plant models and energy grid simulations.

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