Optimum Wind Farm Layouts: A Many-Objective Perspective and Case Study

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Abstract. A steady increase in the prices of non-renewable energy sources, their environmental impact, and the ever-increasing energy demands have made it imperative to explore alternative, renewable energy options. Wind energy is one of the prominent alternatives, and for onshore installations, optimal placement of wind turbines is necessary to harness maximum power. This optimal placement problem, referred to as *wind-farm layout optimization*, has received significant research attention with regards to output power maximization. However, in practice, apart from maximization of power, a number of other key factors need to be considered, such as cabling cost, maintenance cost and noise levels. Furthermore, the wind farm itself may have irregular boundaries and within the area there may be several protected areas due to existing archaeological deposits, water bodies, bird feeding areas, etc. In this paper, we present a framework to support practical layout optimization of wind farms. In the proposed approach, a variable discretization scheme is employed to deal with irregular land boundaries and a many-objective formulation is used to identify the set of trade-off solutions. The utility of the approach is highlighted using a case study resembling the Capital wind farm located in New South Wales, Australia. We hope that this study will motivate use of such tools to solve practical wind farm layout optimization problems.

1 Introduction

Wind power is one of the prominent sources of large scale renewable energy. In 2015, Australia's wind farms produced 33.7 per cent of the country's clean energy and supplied 4.9 per cent of Australia's overall electricity [3]. A typical onshore wind farm contains several turbines installed over a large land area. Each turbine has an individual capacity of producing a certain amount of energy. However, if installed too close to each other, the turbulence and wake effects cause a reduction in wind speed and consequently in the power generated at the downstream turbines. Consequently, a wind farm tends to span expansive land area, which in turn increases its interference with natural habitats [15,23]. Additionally, noise

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generated by the turbines also need appropriate consideration. The noise levels at nearby residential areas should be below prescribed levels to limit potential health hazards [8,28,30]. Wind farm layout design is thus a challenging optimization problem with a number of practical considerations.

Optimum design of wind farm layouts has been attempted in the past with various levels of simplification in the model. For example, in [18] the wind farm was assumed to be of a square shape and represented using a 10×10 grid (100 cells in total), where turbines could only be located at the center of the cells. This discrete location model relied on the size of the cells to inherently enforce proximity constraints (of a minimum distance between any two turbines). Continuous location models have also been used, for example in [13], where turbines could be located anywhere within the area. In reality, a wind farm often spans across areas belonging to multiple land owners and there may be a limit on the number of turbines installed within each block depending on agreements with the respective owners. The model in [32,33] considered straight-line boundaries between these blocks. More realistic models that consider regulatory land use [27] or variation in elevation also appear in recent literature. Irregular boundaries have rarely been considered, although this would be the most likely scenario in a practical wind farm design.

In terms of estimation of power, simplifications range from considering unidirectional wind at constant speed through to models that consider wind speed/direction variation with turbine interactions [22]. Turbine interaction models also vary in complexity ranging from Jensen wake model [12] through to three dimensional wake models [25]. There are also a variety of optimization formulations reported in the literature which range from energy maximization as the sole objective [10,18], energy maximization subject to proximity and noise level constraints [2,9,13] or even bi-objective formulations that consider noise levels and energy maximization simultaneously [14]. Further extensions that consider energy maximization, cable length minimization and enclosed land area minimization have also been reported in [31]. Since the underlying optimization problem is NP-hard, a range of stochastic algorithms (NSGA-II [14], CMA-ES [11], SPEA [13,25], IBEA [17]) have been used for solving it.

Given that the adoption of wind farms clearly depends on a number of factors apart from the power maximization, it is useful to seek and present a rich trade-off set of solutions to the stakeholders. In view of the existing research on this problem discussed above and the associated limitations, the key highlights of this study are listed below.

- Firstly, we offer an optimization framework to deal with wind farm layout optimization involving realistic objectives such as (a) maximization of wind power, (b) minimization of cable length connecting the turbines, (c) minimization of enclosed land area of the layout to reduce maintenance and inspection costs and (d) minimization of noise level. While some of these objectives have been considered individually in the works before, in its essence the problem is a multi-objective optimization problem; also referred to colloquially as a *many*-objective optimization problem (MaOP) when the number of objectives are more than three. MaOP has been a highly active research area in the past decade [16]; but most studies predominantly use mathematical benchmark functions that may not capture some of the real-life modeling challenges. The formulation of the windfarm layout optimization problem as a MaOP, with its unique set of challenges, not only offers opportunity to obtain realistic trade-off solutions, but the case-study can also serve as an application benchmark from an algorithm development perspective.

- Secondly, the proposed approach can deal with realistic constraints such as (a) multiple infeasible regions where turbines cannot be placed due to environmental regulations (archaeological deposits, bird feeding areas, natural flora, etc.) and/or landowners' restrictions and (b) proximity constraints on the turbine placements. Notably, (a) is handled using a novel solution representation through triangulation of the given irregular land area, while (b) is handled through assistance of infeasibility driven constraint handling approach.
- Thirdly, the proposed approach incorporates a mechanism capable of generating a feasible cable layout, i.e., rerouting of cables to avoid all infeasible areas.
- Lastly, the above contributions are demonstrated through a case-study conducted on a problem resembling the Capital wind farm located near Lake George, New South Wales, Australia.

The remainder of the paper is organized as follows. The details of the wind farm layout problem are discussed in Sect. 2. The algorithm is briefly outlined in Sect. 3, followed by the results obtained on the case study in Sect. 4. Concluding remarks and future directions are given in Sect. 5.

2 Wind Farm Layout Optimization Problem

2.1 Generic Problem Formulation

A typical onshore wind farm contains several turbines located over a significant stretch of land. It is well known that the total generated power of a wind farm is significantly less than the summation of the rated power of the individual turbines [26]. This is due to the *wake effect*, where flow past a turbine affects other turbines located downstream from it [13]. The magnitude of wake and in turn the efficiency of energy production depends primarily on the layout of the wind turbines. While maximization of energy production is a key consideration, there are several other factors which affect the design of the layout such as minimization of noise, minimization of cable length, minimization of enclosed area of the layout, etc. Furthermore, there might be several prohibited zones inside the layout where no turbines can be placed due to environmental regulations or landowners' requirements. There are also a number of practical constraints e.g. (a) distance between any two turbines should be more than a prescribed distance (generally 8 times the turbine rotor radius) to minimize wake losses and hazardous loads on the turbines (b) cables between two turbines cannot pass through restricted areas, etc. Thus the layout problem is best represented as a constrained many-objective optimization problem presented in Eq. 1.

$$
\begin{aligned}
&\text{Minimize: } \mathbf{F}(\mathbf{X}) = f_i(\mathbf{X}), i = 1, 2, \dots M \\
&\text{Subject to} \\
&\qquad c_j(\mathbf{X}) \leq 0, j = 1, 2, \dots p \\
&\qquad h_j(\mathbf{X}) = 0, j = 1, 2, \dots q \\
&\qquad \mathbf{X}^{(L)} \leq \mathbf{X} \leq \mathbf{X}^{(U)}
\end{aligned}
\tag{1}
$$

Here, $f_1(\mathbf{X}), f_2(\mathbf{X}), f_3(\mathbf{X}), ...f_M(\mathbf{X})$ are the M objective functions to be optimized; considered here in a minimization sense. The number of inequality and equality constraints are denoted by p and q, respectively. The upper and lower bounds of the variables are denoted as $\mathbf{X}^{(U)}$ and $\mathbf{X}^{(L)}$, respectively. For every solution, the sum of constraint violations is denoted by CV, where $CV = 0$ indicates a feasible solution. For every pair of turbine locations, a violation value is computed if the distance between them is less than 8 times the turbine rotor radius. Sum of these violations correspond to CV. As for the constraints on cable routing, it is managed through a repair (re-routing), as will be discussed shortly. The constraints of being in feasible irregular boundaries is handled implicitly through the solution representation itself.

2.2 Solution Representation

Contrary to some of the regular geometries considered in the literature, e.g. [18], wind farms could typically have geometries with very irregular boundaries. Further, the areas prohibited for turbine installation may be irregular too. In this study, we propose a simple representation that can place the turbines within these irregular boundaries and avoid the prohibited zones. In order to do this, we discretize the boundaries of the allowable areas using the technique proposed in [20] and construct a triangular mesh within the feasible zones. Figure 1(a) illustrates an example of a discretized feasible area with irregular geometry and several infeasible areas with irregular geometries within it such as bird feeding area, private property and a water body. Once the N_t triangles have been obtained through this step, the location of an i^{th} turbine can be represented using the set of variables (A^i,w^i), where A^i is one of the triangles, and w^i is a set of weights such that $\sum_{j=1}^{3} {w_j}^i = 1$. The weights corresponding to a set of uniformly distributed N_w points on a given triangle generated using normal boundary intersection (NBI) [4]. All these points on any given triangle are considered candidate locations for the turbine. The representation is given in Eq. 2.

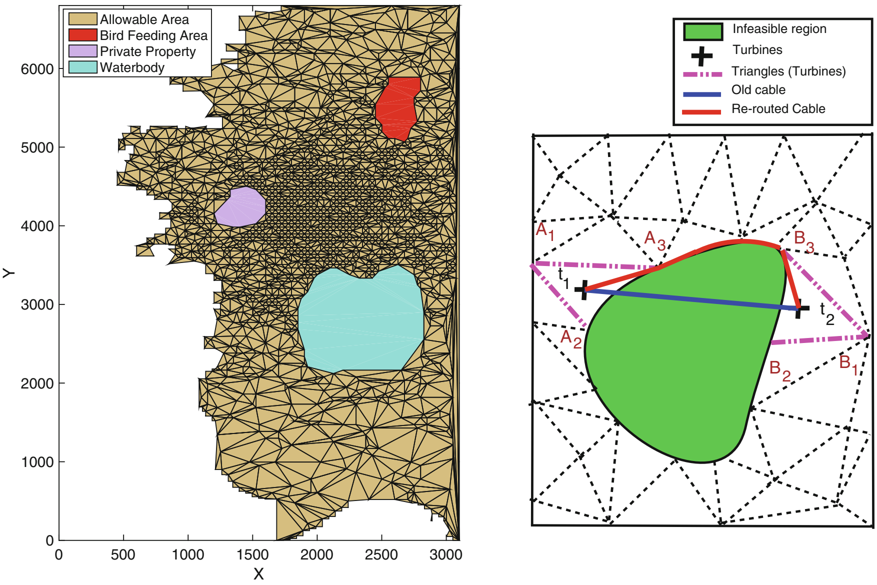

Fig. 1. Discretization of area and cable re-routing (Color figure online)

$$\begin{aligned} &\mathbf{X} = \{A^i, w^i\} \\ &\text{where} \\ &\quad i \in [1, N], \\ &\quad A^i \in \{A^1, A^2, \ldots, A^{N_t}\}, \quad w^i \in \{w^1, w^2, \ldots, w^{N_w}\} \end{aligned} \tag{2}$$

Let's say, the vertices of A^i are $({A_1}^i,{A_2}^i,{A_3}^i)$, the x-coordinate of the vertices of A^i are denoted by $\{x_{{A_j}^i} \mid j = 1, \ldots, 3\}$ and the y-coordinates are denoted by $\{y_{{A_j}^i} \mid j = 1, \ldots, 3\}$. The Cartesian coordinates of the i^{th} turbine location can thus be simply computed as:

$$x_i = \sum_{j=1}^{3} {w_j}^i x_{{A_j}^i}; \quad y_i = \sum_{j=1}^{3} {w_j}^i y_{{A_j}^i} \tag{3}$$

2.3 Objectives and Computation Models

In this study, the performance of a candidate layout is assessed using four objectives: (a) energy production(maximize), (b) total cable length (minimize), (c) enclosed area of the layout (minimize) and (d) the maximum noise level (minimize). The energy production model is based on [13] which considers wind speed and directional variations. Turbines are connected via cables and the total length of the cable configuration contributes to the levelised cost of a farm. Given the location of the turbines, the cable routes are derived using minimum spanning tree algorithm (MST). However, cable connections passing through any of the infeasible regions are re-routed in order to achieve a deployable design. The re-routing of a cable connection between two turbines (t_1 and t_2) is achieved through the following stages. At first, the triangles from the discretized feasible land containing the turbines are identified. Let's say t_1 belongs to the triangle A and t_2 belongs to the triangle B. The vertices of these two triangles (A and B) are (A_1,A_2,A_3) and (B_1,B_2,B_3), respectively. In the next stage, between every i^{th} vertex of A and j^{th} vertex of B, the shortest paths (with path length $\tilde{d}(A_i, B_j)$) through the edges of the discretized feasible area are identified using [7]. In addition to $\tilde{d}(A_i, B_j)$, the distances from every vertex to the corresponding turbines i.e. $d(A_i, t_1)$ and $d(B_j, t_2)$ are added to compute the total distances between two turbines through various vertex combinations. Finally, the re-routed cable length (D) between two turbines is considered as the path having minimum total distance. The total distance computation follows Eq. 4. Figure 1(b) illustrates the infeasible region, the turbines, the triangles containing the turbines, the old cable configuration (in blue) and the re-routed cable configuration (in red).

$$D = \min_{1\leq i\leq 3, 1\leq j\leq 3} \left(\tilde{d}(A_i, B_j) + d(A_i, t_1) + d(B_j, t_2)\right) \tag{4}$$

The maintenance cost of a wind farm is proportional to the enclosed area of the wind farm layout. The enclosed area is computed based on the convex hull bounded by the turbine locations. Generation of noise by the wind farm is one of the most important environmental concerns. In general, the sound level is measured at the receptors at the nearby residences [29]. In this study, the ISO-9613-2 standard has been followed to compute the noise generation at the receptor locations and the maximum noise level generated among all receptors is considered as an objective.

2.4 Case Study Description

The application is based on Capital wind farm located in New South Wales, Australia. The wind farm has three different regions: Groses hill, Ellenden and Hammonds hill. It has a total of 67 turbines out of which 17 are placed in Groses hill, 21 are within Ellenden and 29 turbines are located in Hammonds hill region. There are several infeasible regions, such as woodland vegetation, secondary grassland, wattle woodland, yellowbox woodland, she-oak region and nearby residences as shown in Fig. 2. Due to environmental regulations, turbines cannot be placed in these infeasible regions. The turbines are of same make and model, i.e., Suzlon S88 and the parameters related to the turbines are listed in Table 1. The wind scenario used in this study is constructed from the wind rose provided for the Capital wind farm project in [19].

This problem is solved as a constrained many-objective optimization problem. The need to place 67 turbines translates to 134 variables and results in $67(67-1)$, i.e., 4422 proximity constraints. The discretization of the allowable land generates a total of $N_t = 10476$ triangles among which 2167 triangles belong

Table 1. Turbine related parameters

Turbine parameters	Value	Turbine parameters	Value
Make and model	Suzlon S88	Rated power (P_{rated})	2100 kW
Rotor radius (R)	44 m	Hub height	80 m
Cut-in wind speed (v_{cut-in})	4 m/s	Rated wind speed (v_{rated})	14 m/s
Cut-out wind speed ($v_{cut-out}$)	25 m/s	Slope of the power curve (λ)	262.5
Intercept of the power curve (η)	−1050	Thrust coefficient (C_T)	0.9

to Groses hill, 4639 triangles to Ellenden and 3670 to Hammonds hill. The number of combinations of weights (N_w) for each triangle is set to be 8001. Take note that the discretization does lead to triangles with different sizes and the choice of (N_w) is just to ensure appropriate discretization for the largest triangle. Among the objectives, the noise level at the residences shown in Fig. 2 are computed using the parameters listed in Table 2.

Table 2. Turbine related parameters

Noise parameters	Value
Noise generation (L_w)	105.9 dBA
Residence height	1.5 m
Directivity correction (D_s)	0
Average temperature	10°C
Average humidity	80%
Ground factor (G = 0: hard, G = 1: porous)	0
Nominal midband frequency (f)	{63, 125, 250, 500, 1000, 2000, 4000, 8000} Hz
Atmospheric attenuation coefficient (α)	{0, 0, 1, 2, 4, 9, 29, 104}
A-weighted factors (A_f)	{−26.2, −16.1, −8.6, −3.2, 0, 1.2, 1, −1.1}

3 Algorithm

The optimization algorithm is based on a (μ + λ) evolutionary model, where μ parents are recombined to generate λ offspring and the best μ solutions are selected as parents for the next generation. The pseudo-code of the proposed method is presented in Algorithm 1 and uses *decomposition* of objective space, a strategy commonly used in the contemporary algorithms for solving MaOPs.

The algorithm has a framework similar to reference vector based evolutionary algorithm (RVEA) [1], but there are two key modifications. The first relates to parent selection scheme. While random parents are selected from a neighborhood in RVEA for recombination, we opt to use ranking that prefers marginally infeasible solutions over feasible solutions. Such a ranking scheme was introduced in [21,24] and demonstrated to perform better than strictly feasibility first schemes for constrained optimization problems. Secondly, in order to utilize the advantages of both differential evolution crossover [5] and simulated

Algorithm 1. Proposed algorithm used for windfarm layout optimization

Input: Gen_{max} (Maximum number of generations), W (Number of Reference points/population size), Crossover and mutation parameters

i=1. {Generation counter}
Generate W reference points using Systematic Sampling.
Construct W reference directions; Straight lines joining origin and W reference points.
θ_{th}: Compute the minimum angle between a reference direction and all others.
Initialize the population using LHS sampling P^i; $|P^i| = W$.
Assign individuals of P^i to the reference directions.
while ($i \leq Gen_{max}$) **do**
    Create C offspring from P^i via recombination.
    Assign P^{i+1} individuals from $P^i + C$ to W reference directions
    i=i+1.
end while

binary crossover [6], at each generation both types of crossover are employed for alternate base parents. Similarly during the evolution, reverse order of crossover types are used in alternate generations. Thus, if at generation 1, first reference direction uses differential evolution crossover and second reference direction uses simulated binary crossover, at generation 2 the first reference direction will use simulated binary crossover and differential evolution crossover will be used for the second. The intent is to improve convergence by adopting the high quality solutions generated using the two types of crossovers, while also reducing bias towards either of them. Due to space constraints, we omit the detailed description of the algorithm, but the interested readers are referred to [1].

4 Results

A single optimization run has been performed to solve this problem due to the computationally expensive nature of the underlying simulations. A population size of 220 solutions was evolved over 600 generations to obtain the final layout of the turbines. The run-time was approximately 75 h on a 2.30 GHz, 32 cores with 128 GB of memory. A total of 27 feasible solutions were obtained at the end of evaluation budget, which highlights that the problem is highly constrained. Out of the feasible solutions, 9 solutions were nondominated and there were 3 unique extreme solutions. The extreme solutions in the context of minimum cable length and minimum enclosed area were the same. The obtained values of the maximum energy production, the minimum cable length, the minimum enclosed area and the minimum noise level were 49.16 MW, 53.38 km, 71.07 km^2 and 55.54 dBA, respectively.

The complete set of trade-off solutions are presented in Fig. 3. Since there are only 9 solutions under consideration, the stakeholders can collectively work to select the most preferred option. The layouts corresponding to each extreme solutions including the noise level on each residence is plotted in Fig. 3. In the current state since such modeling/optimization tools are either not readily accessible or well understood by communities at large, there is very limited understanding of the benefits and the impacts of wind farms. The considerations of multiple criteria and resulting visualization can help in an informed decision-making about

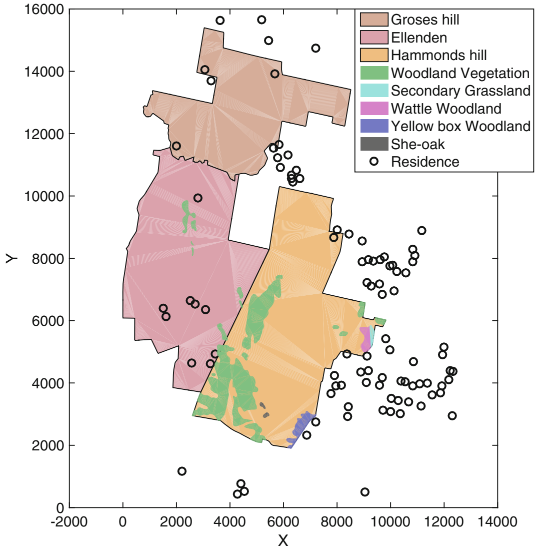

Fig. 2. Wind farm land

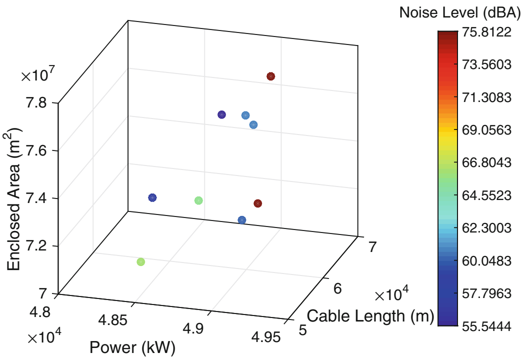

Fig. 3. Nondominated solutions

trade-offs between various designs. For example, it can be observed from Fig. 4 that the location of the turbines corresponding to minimum noise level are away from the residential areas. Among the feasible solutions, there were variations of 1.56%, 14.66%, 8.55% and 26.73% in terms of power generation, cable length, land area and noise level, respectively (calculated as $\frac{\max(|f|)-\min(|f|)}{\max(|f|)}$). This observation raises an interesting and practically relevant design consideration - if one opted to solve the above problem as a single objective power maximization problem, the best solution would correspond to a total power of 49.16 MW with a noise level of 75.81 dBA. On the other hand, using a multi-objective approach one can identify alternatives and opt for a layout with marginally lower power

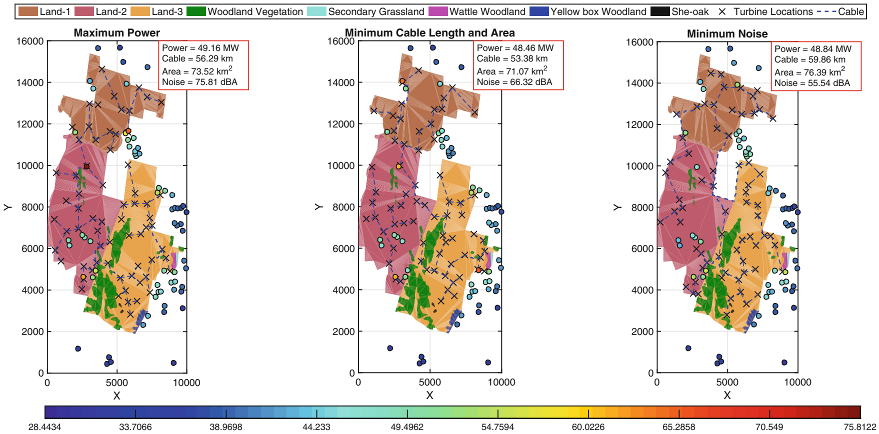

Fig. 4. Layouts corresponding to the best value in each objective

of 48.84 MW but with a significantly lower noise level of 55.54 dBA. That is, by maintaining almost the same level of power output (i.e. only 1.56% lower than the best), one can reduce the noise level significantly (by 26.73%). Since the noise level is often a major community concern that has a major bearing on adoption of the plan, it is important to identify the complete set of trade-off solutions for an informed decision-making.

5 Conclusions and Future Work

In this paper, we presented an approach that can be used to develop wind farm layouts with a range of practical design considerations. Currently, there is limited understanding within the community with respect to the trade-offs involved in a wind farm layout design, as typically the existing studies have solved the problem as a single-objective formulation involving power maximization. In absence of the consideration of multiple objectives and constraints relevant to the environment, the obtained designs may not reflect realistic layouts, which in turn affects the uptake and exploitation of wind energy. In this paper, we presented an approach that can be used to analyze or design potential wind farm layouts with appropriate level of details such as irregular land boundaries, multiple land owners, consideration of protected areas, noise levels at nearby residential dwellings, etc. It also offers an opportunity to view alternative layouts while considering maintenance costs, cable layouts, noise levels and power generation simultaneously. The utility of the approach is highlighted using a case study resembling the Capital wind farm located in New South Wales, Australia. We hope that this study will motivate use of such formulations and tools to identify optimal wind farm layouts.

While in our current analysis we did not impose an upper limit on maximum noise level constraints, it could be a straightforward extension in the future to the existing proximity constraints. Furthermore, variation in elevation of the wind farm was ignored in the model which can be easily incorporated in power estimation models. Apart from its utility as a tool, the underlying problem is also interesting as an application problem for research in evolutionary many-objective optimization as it represents a highly constrained optimization problem with modest number of variables.

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