Determining the Economical Wind Power Sites for the Needed Power Loads Accounting for Geographical Terrains

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Abstract

Green power has attracted the world's attention and the proliferation of wind farms serve this purpose. However, wire connections among power sources and loads can be very costly in addition to the investment on the equipment. The geographical terrains also affect the routing cost, because the connection between two coordinates are often impractical to be a straight Euclidean distance. The Earth is a globe shape with curvature and a terrain can have rugged floors or water surfaces that hinder the convenience of wiring. The objective of this paper is to take advantage of a developed heuristic and apply learning algorithms to determine the best wind power sites. The goal is to conserve wiring expense and accommodate power loads. Terrain knowledge is incorporated by utilizing the geographical databases. Experiments are conducted to demonstrate the approach and justify cost savings. It is expected that this paradigm can be expanded to address more factors and support other green energy application domains.

1. Introduction

On December 12th, 2015, a major international climate agreement on 2 degree Celsius threshold (3.6 degrees Fahrenheit) was supported by representatives from 195 nations at the 21st Conference of the Parties (COP21) to the
The wind energy is one of the great sources of green energy. This natural energy source is abundant for certain areas. It is highly desirable to install wind turbines at locations with strong wind and low wire connection cost. A number of researches [3] [4] [5] had been conducted to find the shortest network connectivity. The Menger’s theorem [6] further theorized n-connected network. The study in [7] extended the n-connected problem to account for different types of nodes, power sources and loads. The objective was to promote fault tolerance capability for loads in case of a wire corruption, and the problem was proven to be NP-hard [8].

Traditionally, the cost estimation for a connection network was often a function of the total Euclidean distances. However, the geographical environment in reality may dominate the cost significantly for a power network. Since a terrain can contain hills, lakes and more in addition to planes, the cost can greatly be driven up by rugged surfaces and the obstructions between straight-line connected locations. Intuitively, it is more expensive to connect wires across a lake than a plane. A connection going up/down a slope is considered laborious and demands more materials than doing so on a horizon. In other words, terrain characteristics play an important role in practice and dictate a non-negligible cost of an energy network.

The objective of this paper is to identify the most economical wind power source locations to support loads and minimize the cost for the entire power network. A cost heuristic function was developed to address three critical terrain features, including the steepness of slopes, the area of water surfaces and the curvature of globe distances, to optimize wire connection between two Earth locations. This study utilizes the cost heuristic and applies artificial intelligence to search the best locations for installing wind turbines. The power loads are at stationary locations to represent the already known energy consumption sites, such as towns and cities.

The organization of the paper is as below. Section II describes the cost heuristic function according to the knowledge of terrain data. The construction of an energy network is discussed in Section III. Section IV introduces our artificial learning algorithm to find the best economical solution to allocate wind power sources. Experiments are conducted and discussed in Section V. Section VI concludes our work.

2. Terrain Data and Cost Estimate

The US Geological Survey (USGS) government website provides portals and collections for maps, data, and imagery. For geographical information, the USGS web service [9] provided elevation data and some online shape files [10] offered water body knowledge. For a terrain of interest, the map was first partitioned into cells. The cost $C_{c,n}$ from a current cell $c$ to its neighborhood cell $n$ was estimated by the following heuristic function.

$$C_{c,n} = d_{c,n} \cdot \exp(w_1 (1 - s_{c,n}) + w_2 (r_p + r_n^p) / 2)$$

where $d_{c,n}$ is the sphere distance between two Earth coordinates computed according to the Haversine formula [11], $s_{c,n}$ is the slope angle yielded from the inner product of two vectors: the elevation difference and the horizon, $r_p$ and $r_n$ are the ratios of cells’ water surfaces with a power $p$ to emphasize the significance, and finally $w_1$ and $w_2$ are the user specified weights to adjust the expense of elevation vs. water ratio. Note that the water ratios are averaged, so that the cost is not biased by the traversal direction.

For this heuristic function, the cost is dominated by the actual globe distance. Besides, the steeper is a slope either up or down, the costlier is the wiring so that the cost function is exponential not linear. This thus favors the flat surfaces like planes or plateaus to be the high priority choice for wire connection. Similarly, higher water surface ratios will boost up the cost exponentially. Note that water surfaces are flat but undesirable. Therefore, the two weights play an important role for the linear combination of both factors in the argument and can be carefully arranged to account for real circumstances.

With the heuristic to estimate cost between cells, the A* search algorithm [12] was then adopted to flood fill the map to efficiently find the best route between two Earth coordinates. The efficiency of A* came from the consideration of cost by two parts, i.e., $f(n) = g(n) + h(n)$. Function $g(n)$ is by far the lowest cost during search from
the starting cell to cell $\zeta_r$ in a route according to the aforementioned heuristic function. The $h(n)$ is the A* algorithm's prediction cost estimate to traverse from cell $\zeta$ to the final destination cell and is calculated as their globe distance. The purpose of this prediction estimate prevents the miss of a nearby destination. Greedily, the traversal favors the next move to go toward the direction of the destination by expecting that path to be cheaper in cost. Once the cost is accumulated to become higher than other wait-to-be explored routes, the algorithm turns to attempt the other alternative routes first.

3. Construction of Energy Network

The construction of the entire power network will connect all of the wind power sources and power loads together. The goal is to minimize the total connection cost and the strategy is to exploit the foundation work in Section II. Algorithmically, the minimum spanning tree (MST) [13] yields the shortest Euclidean distance to connect all nodes, regardless of the direction. For the cost heuristic in Eq. (1), the computation result is also non-directional, because the slope is invariant and the water surface ratios account half of both cells. As a consequence, the MST algorithm can be easily adopted by replacing the distance function for every two nodes with the derived A* cost function.

To improve performance, the Delaunay triangulation algorithm [14] can be applied beforehand to partition the entire map into triangles. This reduces the computation time for every pair of nodes in the MST algorithm, unless they are connected in a triangle. However, two nodes that are short in Euclidean distance may have a high cost for connection. The solution is to replace the normal Euclidean distance with the A* calculated cost for every edge and render virtual triangles based on those costs. The Delaunay algorithm will sort the edge costs and greedily choose the next available lowest cost edge for triangle construction. Combined with the MST, the least expensive energy network can be rendered.

Since this work focuses on finding the ideal wind power sites, their locations are thus not stationary, making the construction of cost saving energy network difficult. To simplify the matter, the wind farms will be user drawn polygons on a terrain that enclose cells with each one being a potential site for a wind turbine. Every enclosed cell is assumed to have the same class of wind intensity. Each wind farm is default to have at least one wind turbine, even though the default value can vary individually. The total number of turbines is justified by the user to meet the needed loads. The problems are then reduced to decide how many wind turbines should be placed in each farm and where the wind turbines should be located? The next section introduces our methodology.

4. Swarm Intelligence Learning Algorithm

To determine the number of wind turbines and their locations in a wind farm, the ant colony swarm intelligence approach [15] is our adopted learning paradigm. The good cooperation of ants soon forms a pattern to guide the ants in the next iteration to follow. Ants generally leave pheromone to help others make decisions and after scent dissipation may wander to other directions. It is this phenomenon that prevents the global behavior from stocking at a sub-optimal solution. Nevertheless, ants may not accomplish a common goal if no pattern is found. This is often the case if they run into wide-open random behavior. The proposed methods carefully prevent this.

The algorithm first computes the lower bound network cost $C_0$ with only power loads. Next, a base scenario is created with all wind farms having an equal opportunity to share the number of wind turbines. Because cost is lower when power sources are close by, the wind turbines in each farm are best located in the neighborhood cells. The base network cost $C_b$ is then computed. The ultimate goal is to lower the cost of $C_b$ to approach as close to $C_0$ as possible.

Assume there are $m$ ants in the system. Each ant begins with adjusting the list of wind turbine distribution for the wind farms. There is a probability of $(1 - p)$ that instead will recreate a new list of distribution according to the number ratios of the current list $N = <n_1, n_2,$
Eq. (3) uses a random value \( q, 0 \leq q < 1 \), to reallocate a turbine to one of the wind farms. By invoking it \( \sum_{i=1}^{n} n_i \) times, a new list of distribution \( \vec{n} = (\vec{n}_1, \vec{n}_2, \ldots, \vec{n}_w) \) is derived. The number of wind turbines are thus rearranged to those farms based on the new list.

\[
\vec{n}_k \leftarrow \vec{n}_k + 1, \quad \text{if} \quad \frac{\sum_{i=1}^{k} n_i}{\sum_{i=1}^{w} n_i} \leq q \leq \frac{\sum_{i=1}^{k} n_i}{\sum_{i=1}^{w} n_i}
\]

The scent \( \tau(x, y) \) is initialized with \( \tau_0 = 1 / ((C_0 - C_0) \cdot m) \) for the installation of a wind turbine at cell \( z(x, y) \) of location \((x, y)\). An ant will obey its own distribution list to pick the correct number of wind turbines for each wind farm, and the scent of a chosen cell is modified through local trail updating with \( \alpha = 0.1 \).

The selection of a cell location in a wind farm \( f_k \) follows a greedy approach by giving a good chance \( q_0 \) to pick an available cell with the highest scent value. Eq. (5) formulates the selection, where \( 0 \leq q_1, q_2 < 1 \). The site location \((u, v)\) with the highest scent is selected if \( q_1 \) conforms to the chance \( q_0 \). Otherwise, a site \((x, y)\) is chosen based on another random value \( q_2 \).

\[
(x, y) = \begin{cases} 
\text{argmax}\{\tau(u, v)\} & \text{if} \ q_1 \leq q_0 \\
(x_i, y_i) & \text{if} \ q_1 > q_0 
\end{cases}
\]

The chosen cell is stored into the working memory \( M_k \) for wind farm \( f_k \). Let function isNb\((M_k)\) return a set of candidate locations that are not in \( M_k \) but are an eligible neighbor to one of the elements in \( M_k \). The subsequent site choices will also need to verify with this function, as shown in Eq. (6).

\[
(x, y) = \begin{cases} 
\text{argmax}\{\tau(u, v)\} & \text{if} \ q_1 \leq q_0 \\
(x_i, y_i) & \text{if} \ q_1 > q_0 
\end{cases}
\]

Once ants are done with determining the number of wind turbines for and their locations in the wind farms, their individual energy network construction cost can be computed for comparison. The most economical solution is adopted for reinforcement learning to form a global pattern. Let \( C_i \) be the best network cost solution in iteration \( i \) by ant \( a_j \). The scents of all the chosen cells are modified through global trail updating in Eq. (7) with same \( \alpha = 0.1 \). The reciprocal of cost difference, \( (C_i - C_0)^{-1} \), implies more pheromone is added whenever the solution \( C_i \) reaches closer to the lower bound \( C_0 \).

\[
\tau(x, y) \leftarrow (1 - \alpha) \cdot \tau(x, y) + \alpha \cdot (C_i - C_0)^{-1}
\]

5. Experiments and Results

Experiments are conducted to evaluate the capability of cost saving for the developed algorithm. The NY state Finger Lakes region is chosen for study due to its sophisticated geographical characteristics. The longitudes range from -77.950838 to -75.850868, and the latitudes from 42.293404 to 43.431465. The region is decomposed into a dimension of 200 * 360 cells, so a cell is closer to a square. For the A* algorithm in Eq. (1), the weights and power are \( w_1 = 2, w_2 = 4, \) and \( p = 0.5 \). The higher weight value \( w_2 \) than \( w_1 \) implies water surface is more costly than slope for wire connection.

For the swarm intelligence learning algorithm, 15 ants cooperate with each other iteratively to find a cheaper solution for the best placement of wind power sources. There are 100 randomly generated power loads and 300 wind turbine power sources allocated to 6 wind farms. Figure 1 shows the user drawn polygons to be the wind farms and the locations of wind power sources are enclosed inside. This is a result after more than 1500 iterations. In the beginning, the number of wind turbines are evenly distributed. However, five of the wind farms cover water surfaces. Therefore, if a wind turbine is accidently placed in water, the network construction cost will become high. A few iterations of the cooperating ants will quickly fix the situation. The poorly located power sources are soon moved to dry and flat spots to conserve cost. However, the number of wind turbines in a wind farm is not a fixed value. Certain wind farms may offer more advantages to reduce network connection expense. For the Finger Lakes region, the terrain on the south is pretty rugged, making the north wind farm closed to the city Rochester the most favorite choice. Consequently, the best found solution reveals this phenomenon.
Figure 1: A power network by swarm intelligence learning result for the Finger Lakes region

Figure 2 shows the cost reduction after thousands of iterations. The base solution $C_b$ has almost two times higher cost than the lower bound solution $C_0$. After one iteration, the ants significantly lower the cost to only 1.13 times. A very good solution is actually found after around 200 iterations, resulting in a further cost saving only 1.07 times of the lower bound solution. Due to limited space for figures, we also like to emphasize that other experiments with a diverse number of loads, sources, and ants all yield a compelling cost saving. More importantly, the wind power source sites are soon placed at dry and smooth spots and the solution is quickly converged after a reasonable amount of iterations.

Figure 2: The cost saving trend corresponding to the number of iterations

6. Conclusions and Future Work

Green power is undoubtedly the future trend and the energy connection network must be economical to support this direction. Our study had successfully accounted for actual sphere distance and geographical characteristics of the modeled terrain to connect two Earth coordinates. This study greatly expands the foundation work to determine the best power source locations to construct an economical energy network. Combined with our cost heuristics, the MST and Delaunay triangulation algorithms are revised to find the optimal solution accounting for terrain characteristics. The ant colony swarm intelligence learning algorithm are further applied to efficiently and effectively identify the best money saving locations for wind power sources. Experiments show that cost saving is evident and the system can quickly converge to a good solution.
The future work will intend to relax some assumptions, including setting no limit on the number of wind farms and incorporating real wind data for location selection. It is also vital to balance the power source locations to meet power load demands of sub regions. Besides, extra power hubs similar to Steiner points [7] are likely to be added to the system to further reduce the network cost. It is our expectation that other green energy domains can benefit from these studies.

References


