Optimal Path Planning for Drone Inspections of Linear Infrastructures

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Abstract: Autonomous Beyond Visual Line of Sight (BVLOS) flights represent a huge opportunity in the drone industry due to their ability to monitor larger areas. Autonomous navigation and path planning are essential capabilities for BVLOS flights. In this paper, we introduce the routing component of a path planning system for inspecting linear infrastructures. We explore both a *direct algorithm* and a *transformation algorithm*. The direct algorithm is an extension of A* to allow limited routing through air as well as the use of non-logic intersections. The transformation algorithm pre-computes a graph that include edges for routing through air and nodes for non-logic intersections. We implemented both algorithms for routing along a particular type of linear infrastructure, power lines, and validated them through an empirical evaluation at three different scales: the Danish power grid, the French power grid, and the entire European power grid. The test results show that the transformation algorithm allows for sub-second routing performance for a small-to-medium sized power grid. Larger power grids can be routed in less than five seconds, and even an optimal route of more than six thousand kilometers along linear infrastructures from Portugal to Sweden via Russia is found in less than half a minute. All algorithms have been implemented and are available as an open-source Python package for Linear-infrastructure Mission Control (LiMiC).

1 INTRODUCTION

There are more than 200,000 km (University of Southern Denmark,) of overhead power line cables in European countries that are the backbone of the energy infrastructure. According to ((Mrs.),), a heavy windstorm, which caused a tree to fall on an important power line in Switzerland, resulted in around $1.2 billion worth of damage. Approximately 56 million people – mainly in Italy but also in Switzerland – were without power for several hours ((Mrs.),). Thus, in order to prevent power outages, electric utilities regularly perform inspections of their power grids to plan for the necessary repair or replacement work (Nguyen et al., 2019).

To improve the inspection speed, accuracy, safety, and costs, a considerable amount of research has been conducted in order to automate inspections by using drones. Drones have been used in various areas such as infrastructure inspections for automating labor-intensive, time-consuming, and sometimes even dangerous tasks. However, the current applications of drones in the area of inspecting linear infrastructures such as power lines still face many unsolved challenges such as drone flight time as well as autonomous BVLOS flights.

The BVLOS flights represent a huge opportunity in the drone industry especially in the field of linear infrastructure inspection due to their ability to monitor larger areas. During a BVLOS flight, the drone often flies out of the visual range of the Pilot-in-Command. Thus, extra safety features such as the capability to autonomously navigate and path planning have to be considered on the drone to prevent the aircraft from flying beyond the restricted area assigned by the Special Flight Operations Certificates (SFOC)(Fang et al., 2018).

The core task of autonomous navigation and path planning for linear infrastructures is optimal routing, i.e. finding the shortest path along the infrastructure between two given elements of the infrastructure. This task is very important not only for routing drones from one location to another, but, more importantly, also as the basic building block of other tasks such as optimal scheduling of inspection missions. For practical purposes of mission control for drone inspections, we aim as a design goal for the routing algorithm to run in less than one second.

New EU regulations for drone inspections have ease the process of obtaining permission to fly inspection missions for the special case of inspecting linear

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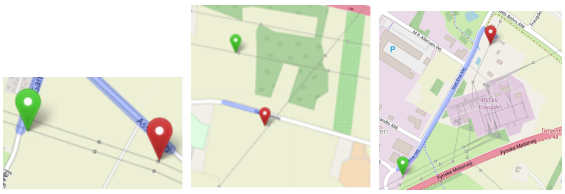
infrastructures. These regulations require the drone to stay within close range to the linear infrastructure (world,). Thus, finding an optimal route requires considering many factors such as minimizing the flight time a drone spends away from the immediate vicinity of the linear infrastructure. This factor can be represented through a cost function that penalizes flying away from the linear infrastructure and, thus, affects which route is considered optimal.

There are standard solutions for routing in road networks. The Open Source Routing Machine (OSRM) (Huber Stephan, 0601) is an open-source C++ implementation of a high-performance routing engine for finding the shortest path in such a network, and it is available as a light-weight docker image for straightforward deployment.

In the case of power line inspections considered in this paper, we can view the optimal routing problem along linear infrastructures as a search problem for finding a path with a minimum cost between two power towers, including possibly limited routing through air and the use of non-logical intersections. This search problem poses several significant challenges, which effectively preclude the use of pre-existing routing solutions such as OSRM:

- The start and end power towers are on different parallel power lines. (see Fig. 1 (a)).
- There is an intersection between power lines, and the start and end power towers are on these lines. (see Fig. 1 (b)).
- The lines intersect with no-fly zones (e.g. around airports) or infrastructure to be avoided (e.g. transformer stations, power plants). (see Fig. 1 (c)).



(a) Parallel points (b) Intersection (c) Power substation

Figure 1: Path planning challenges.

In Fig. 1 (a), the start and end power towers are on two parallel power lines. In order to find a path between these two power towers, one might be tempted to use OSRM with a profile for drones that use power lines instead of streets. The result of such a routing is shown in Fig. 2.

The route computed by OSRM starts from the star power tower and follows the line until it arrives at a transformer substation. From the substation, it routes

Figure 2: Path planning by using OSRM.

within the transformer substation to the other power line and follows that one until it reaches the end power tower. It is immediately apparent that OSRM cannot find the shortest path between these two power towers, and that it only finds a path due to the two power lines being logically connected through the transformer station.

In the case of Fig. 1 (b), OSRM cannot find a route as the two power lines are logically never connected. In both Fig. 1 (a) and (c), a route computed by OSRM would require the drone to fly through a transformer station. This is undesirable for a multitude of safety reasons. Due to these problems, we could not use OSRM or similar pre-existing solutions for optimal routing.

In order to solve these problems, we have implemented two algorithms to compute the shortest path between two elements of a linear infrastructure such as power lines: (1) a direct algorithm based on an extension of the A* algorithm for finding the shortest paths in weighted graphs as well as (2) a transformation algorithm for transforming the special conditions of the problem into a standard weighted undirected labelled graph.

The direct algorithm extends the A* algorithm by allowing to route between two nodes not connected through an explicit edge with certain restrictions: routing through air is penalized by having a higher cost factor and is allowed only up to a certain distance to take into account regulatory restrictions. Furthermore, given that the edges of our graph are on an essentially two-dimensional surface, they might intersect. Thus, the algorithm also has to find intersections and use them to change from one power line to another without having to fly away from the power lines.

The transformation algorithm builds on the same ideas as the direct algorithm but pre-computes a graph of power towers. The nodes of the graph are locations typically representing power towers. The edges of the graph are weighted by the distance between two connected power towers. There are also edges connecting power towers through air with scaled weights to model higher costs. Finally, there are nodes representing non-logical intersections of power lines. An optimal route between two power towers then corresponds to the shortest path between two nodes in the

graph, and it can be found by using standard graph algorithms such as the A* algorithm.

The rest of this paper is structured as follows: Section 2 presents and explores the direct algorithm, including how to speed up repeated calculations and queries to the map data through various caching schemes and the use of multi-threading. Section 3 presents and explores the transformation algorithm for optimal routing which allows the use of standard shortest path algorithms, including different pruning methods for removing redundant edges in the graph. Sections 4, 5, and 6 illustrate the results of the empirical evaluations on the Danish, the French, and the European power grids. Section 7 concludes this paper and discusses possible future work.

2 THE DIRECT ALGORITHM

This section presents and explores the direct algorithm, including how to speed up repeated calculations and queries to the map data through various caching schemes and the use of multi-threading.

2.1 The Extension of A* to Route through Penalized Air and to Consider Non-logical Intersections

The A* (pronounced "a star") algorithm(Duchoň et al., 2014) is a popular choice for path planning problems, as it is guaranteed to return an optimal solution and can be used in a wide range of contexts. It combines the speed of heuristic approaches like Greedy Best-First-Search (Dechter and Pearl, 1985) and optimal approaches such as Dijkstra's algorithm (Noto and Sato, 2000). The A* algorithm begins with the start node and successively computes the exact cost of the path from the starting node to any other node n represented as a function $g(n)$. In order to select which n to expand next, A* employs a heuristic based on the estimated cost from node n to the end node represented as $h(n)$. When the end point n_{end} is reached, the A* algorithm terminates. The cost is then known through $g(n_{end})$, and the path representing the corresponding route can easily be reconstructed through a simple bookkeeping exercise. As long as the heuristic function h is admissible (i.e., it underestimates the costs to the end node), the cost and route found by A* are guaranteed to be optimal.

In (Sathyaraj, 2008), authors compare the A* algorithm with Dijkstra solver and Floyd-Warshall algorithm in the term of the increasing number of nodes visited and the time of computation consumed. As, in the worst-case, the Dijkstra algorithm has to consider all paths to all possible nodes, the time complexity of that algorithm depends on the number of nodes and edges in the graph. However, the time complexity of the A* algorithm does not depend on the total number of nodes(Sathyaraj, 2008) but only on the length of the shortest path and the average branching factor. The Floyd-Warshall algorithm computes the shortest paths between all nodes. On large sparse graphs such as the ones representing linear infrastructures, this is prohibitive in terms of time and space requirements. In (Sathyaraj, 2008), authors concludes that the A* is the best-established general algorithm for finding optimal routes.

The variant of the A* algorithm proposed in this paper has several parameters:

- **SafeDist:** the minimum distance to keep from perilous infrastructure such as transformer stations
- **MaxFly:** the maximum free flying distance away from infrastructure elements such as power towers
- **Penalty:** the penalty factor for flying away from infrastructure elements
- **Precision:** when set to larger than 1, the algorithm will perform faster but find possibly non-optimal routes

The **SafeDist** parameter has two functions: it makes the drone avoid infrastructure elements such as transformer stations, and it avoids unnecessary routing complexity, as transformer stations internally consist of a large number of logical and non-logical intersections and, consequently, increase the average branching factor. We use a default value of 100 metres.

For the **MaxFly** parameter, we set a default of 1000 metres, which again has two effects: it disallows flying away from power towers for more than 1 km, and it keeps the average branching factor on a somewhat manageable level. In our initial experiments, we found that a much lower value would sufficie for most situations. But there are situations such as flying around a transformer station or crossing over to a line, where free flights of up to a few hundred metres were necessary to avoid having to add tens or hundreds of kilometres.

The **Penalty** parameter is used to penalize such free flying time away from power lines. We use a default value of 20, as we would rather have the drone fly for an extra kilometre than have it fly 100 metres away from the power lines.

The **Precision** parameter scales the estimate for $h(n)$. We use a default value of 1, as we strive for fully optimal routes in order to keep flying times for the drones minimal.

Fig. 3, shows the UML diagram of the direct A* algorithm. As shown here, the algorithm finds the nearest power towers to the start and end points selected by the user. In this algorithm, we have a priority queue of power towers to visit called the `TODO` list. The power towers in the queue are sorted by their f-value, i.e., by their estimated total costs. The algorithm is executed until the queue is empty or the least costly element of the queue is equal to the endpoint. In the beginning, we add the start power tower to the `TODO` queue with the g-value set to zero and the f-value set to the distance between the start and the end tower multiplied by the **Precision** value. For example, in the beginning, the queue contains the following information:

`(dist=320.89,tower=pylon(id=831295194, latlon=(55.3466014, 10.447012),neighbours=()))`. Here, `dist` is the f-value and `pylon` is the class we use to hold the id, GPS location, and possibly neighbours of intersections.

Then for the most promosing item in the `TODO` queue, the algorithm finds all the direct neighbors of the tower as well as all other towers within **MaxFly** distance. Only the neighbours which are safe according to **SafeDist** are kept. The g-value and h-values are computed, the g-values are scaled by the **Penalty** factor.

The algorithms divides the neighbours into power towers on the same line (direct neighbours) and those that are not (indirect neighbours). Then it calculates possible intersections between the power line segments between the current tower and its direct neighbours and the segments between indirect neighbours. Given that these towers are in close proximity, we compute possible intersections using a standard formula for intersections in a plane. The formula computes the intersection of the infinitely long lines containing the segments represented by the coordinates of the four power towers - (x_1, y_1) and (x_2, y_2) for the direct segment and (x_3, y_3) and (x_4, y_4) for the indirect segment. Here, d is the denominator used and 0, if the segments/lines are parallel. Otherwise, t and u compute whether the intersection is on the segments ($0 \leq t, u \leq 1$). If the intersection is on the segments, the intersection coordinates x and y can be computed.

$$d = (x_1 - x_2) * (y_3 - y_4) - (y_1 - y_2) * (x_3 - x_4)$$
$$t = \frac{(x_1 - x_3) * (y_3 - y_4) - (y_1 - y_3) * (x_3 - x_4)}{d}$$
$$u = -\frac{(x_1 - x_2) * (y_1 - y_3) - (y_1 - y_2) * (x_1 - x_3)}{d}$$
$$x = \frac{(x_1 * y_2 - y_1 x_2) * (x_3 - x_4) - (x_1 - x_2) * (x_3 y_4 - y_3 x_4)}{d}$$
$$y = \frac{(x_1 * y_2 - y_1 x_2) * (y_3 - y_4) - (y_1 - y_2) * (x_3 y_4 - y_3 x_4)}{d}$$

The above approach for computing the shortest path is very slow in practice due to the large number

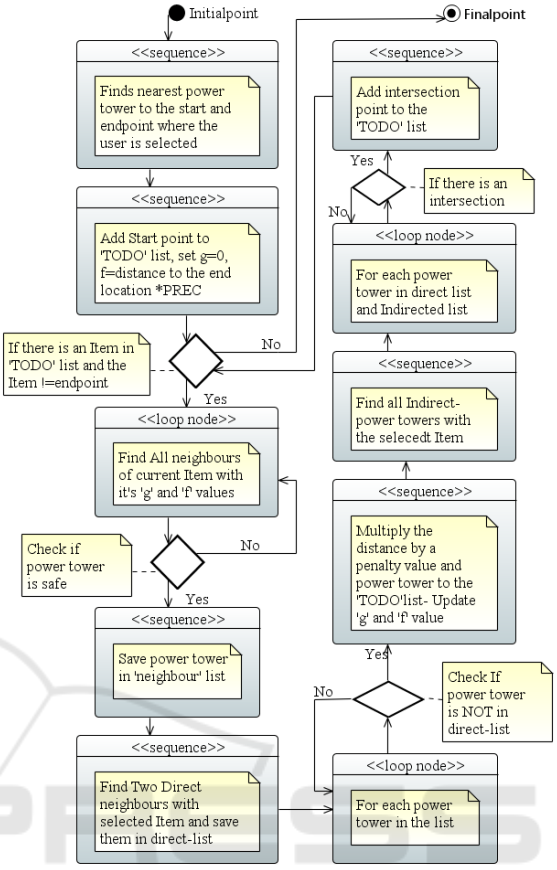


Figure 3: UML Activity diagram of the direct algorithm.

of web-service requests to the overpass API. In the next subsections, we explain about how to use a disk-based cache file and a memory based-cache file in order to cache web-service requests in order to speed up the shortest path calculations.

2.2 Speeding Up Repeated Calls and Calculations through a Disk-based Cache

In order to speed up the performance of the algorithm, our first attempt was to employ a disk-based cache for storing information persistently. In this case, we have used the `dogpile.cache` module. A `dogpile` lock allows a single thread to generate an expensive resource while other threads use the “old” value until the “new” value is ready(python library,). The `dogpile.cache` module provides an interface to caching backends of any variety. The DBM file backend uses a lock-file alongside a Unix-style DBM file. A lock file is used to protect the DBM file itself from concurrent writes and for coordinating the value creation. A cache in the `dogpile.cache` framework

consists of a region, a backend, and value generating functions. A region is an instance of the cache region class and defines the configuration details for a particular cache backend. A backend describing how values are stored and retrieved from a backend. Finally, data generation functions are user-defined functions that generate new values to be placed in the cache.

In this research, the data generation functions generate new values by requesting data through overpass API. we have used `@region.cache_on_arguments()` as a decorator function for these functions for fully-transparent querying and updating of the cache. For instance, the `find_neighbours_id` function sends the following query for finding the locations of all power towers on the same power line as power tower with id `1881623946`:
https://overpass.kumi.systems/api/interpreter?data=[out:json][timeout:3600];(node(id:1881623946);way(bn)[”power”=”line”];node(w););out;
The code below exemplifies how we use `dogpile.cache` in this paper. We have defined a region which uses a file `astar.dbm` as a backend for storing and retrieving data. ”@region.cache_on_arguments()” on the top of the ”find_towers” function is used for updating the “astar.dbm” cache file.

```
region = dogpile.cache.make_region()
    .configure("dogpile.cache.dbm",
        arguments={"filename":"astar.dbm"})

@region.cache_on_arguments()
def find_neighbours_id(location, around):
    return (towers);
```

In the next subsection, we explain how to use a memory-based cache with a persistence layer as well as how multi-threading can be used to pre-fill the cache file.

2.3 The Pre-filling of a Persistent Memory-based Cache

As we mentioned in the previous section, in order to increase the speed of path planning, we have employed a disk-based cache. In this section we explain how to use a memory-based cache instead. We have decided to use a memory-based cache, as the loading of cache data from a disk and the locking mechanism are both rather slow compared to loading the cache data from the memory.

Python’s standard perstistence layer `Pickle` can be used to serialize and deserialize a Python object structure. In this research, we have used `Pickle` for loading the dictionaries that serve as backend for memory-based caches in `dopgile.cache`. Unpickle is used to open the cache file for reading. The following code shows how the cache data is saved and loaded.

```
# saving cache file to astar.cache
pickle.dump(region.backend._cache,
    open("astar.cache","wb"))
# load cache file to the region
region.backend._cache = pickle.load(
    open("astar.cache","rb"))
```

Table 1 shows times for picking and unpickling different file types in seconds. Not compressing (None) is the fastest choice for both saving and loading file. Compressing with gzip is a good compromise, when the focus is on fast loading and reasonable file size. Pickling and unpickling times for xz, which produces the smallest file size, are highest compared to other options.

Table 1: Time for pickling and unpickling different files.

Compression	Size	Pickling (seconds)	Unpickling (seconds)
None	368,318K	12.845	28.538
gzip	153,148K	84.380	35.121
bz2	145,436K	45.494	43.844
xz	102,099K	159.424	46.912

In the next subsection, we explain about using multi-threaded for pre-filling the cache.

2.4 The Multi-threaded Pre-filling of the Cache

A thread of execution is defined in computer science as the smallest sequence of programmed instructions that can be scheduled in an operating system. Multi-threaded programs run faster on computer systems because these threads can be executed concurrently. Threads of the process share the memory of the global variables. If the global variables change in one thread, this change is valid for all threads.

The `concurrent.futures` module in Python 3 provides a high-level interface for asynchronously executing “callables”, typically functions with parameters. The asynchronous execution can be performed with threads using the `ThreadPoolExecutor` class. An `Executor` object uses a pool of at most `max_workers` threads to execute calls asynchronously.

In this research, we used multiple threads for pre-filling our cache, allowing to submit multiple Overpass queries simultaneously to the server. The code bellow illustrates this multi-threaded approach for pre-filling the cache.

```
import concurrent.futures as cf
exe = cf.ThreadPoolExecutor(max_workers)
exe.submit(find_all_neighbours, tower,
            around, safe_dist))
```

In the next section, we explain the implementation of the transformation algorithm for routing.

3 THE TRANSFORMATION ALGORITHM

This section is split threefold. In the first subsection, we explain about extracting the graph from the memory-based cache file which we have created by multi-threaded pre-filling in the previous section. In the second subsection, we use two functions (`prune_complete` and `prune_incomplete`) for pruning the redundant edges in the graph. In the third subsection, we use standard A* implementations on the graph for routing.

3.1 Extracting a Weighted Undirected Graph Including Non-logical Intersections and Penalized Air

A weighted labelled graph G is a set of nodes N labelled by a function ℓ connected by edges E weighted by a function $w(e)$. It can be represented as $G = (N, E, \ell, w)$. The nodes N in this research are labelled with power tower GPS locations from the map. Two nodes $n_1, n_2 \in N$ are connected by an edge $e^d = (n_1, n_2) \in E$ if there is a power line between these two locations. This edge is labelled with a weight that represents the distance between the two locations, i.e., $w(e^d) = \mathsf{distance}(\ell(n_1), \ell(n_2))$ where we use the Haversine distance function for distance. There is also an edge e^i between two nodes $n_1, n_2 \in N$ if $\mathsf{distance}(n_1, n_2) < \mathsf{around}$. In this case, such an edge $e^i = (n_1, n_2) \in E$ would be labelled with the penalized distance, i.e., $w(e^i) = \mathsf{penalty} \times \mathsf{distance}(\ell(n_1), \ell(n_2))$.

A path through a graph is a traversal of the consecutive nodes along a sequence of edges (Sathyaraj, 2008). The length of the path is the sum of the weights of edges that are traversed along the path. The best path is the one which has the minimum sum of the weights from the source to the destination.

Path planing is the determination of all possible paths from the start point to the endpoint and it is the art of deciding which path to take. This decision is based on the length of the path. Therefore, path planing depends on factors including how to get from the starting point to the end, how to get around obstacles in the way and how to find the shortest possible path. (Sathyaraj, 2008).

Different methods have been developed to solve this problem and find the shortest path such as the unidirectional A*, the bidirectional A*, the Floyd-Warshall (Hougardy, 2010), and the Dijkstra's algorithm. Standard graph packages such as `networkx` support all these algorithms. We use `networkx` for generating the shortest path in the graph of power towers as we found it to have better out-of-the-box performance than competitors such as e.g. `graph_tool` (graph tool,).

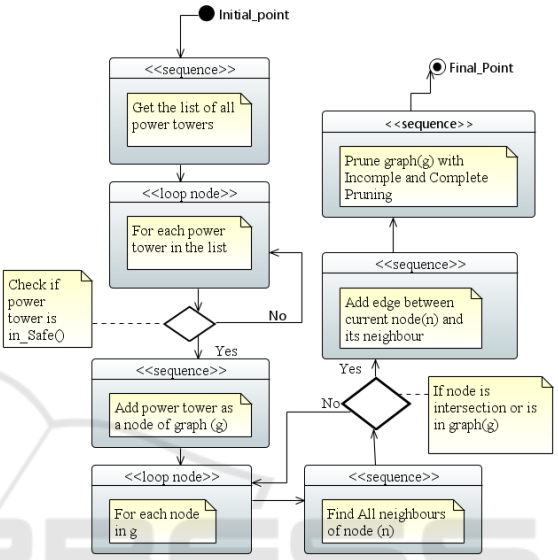


Figure 4: UML Activity diagram of extracting graph.

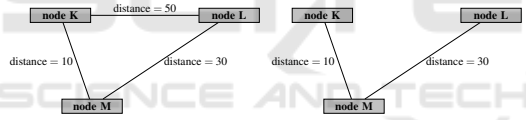
Fig. 4 shows the UML diagram for extracting the graph. In this research, we have created a graph of power towers for each European country. First, we send an overpass API request to get the list of all power towers for the specific European country. Then for each power tower in the list, the algorithm checks if the power tower is in a safe distance from power substations. If this is the case, it adds the power tower as a node of the graph. For adding the edges between nodes the algorithm finds all direct and indirect neighbors of the current power tower with their distance. The algorithm is also creating non-logical intersection points in the graph and adds edges between these points and the current power tower. We also use two functions `prune_complete` and `prune_incomplete` to remove edges that can never be part of a shortest path. This increases the performance of the transformation algorithm. We explain these functions in the next subsection.

3.2 Incomplete and Complete Pruning of Redundant Edges

Pruning of redundant edges in this research is used to improve the search performance on the graph by eliminating redundant edges, i.e., edges that have such a high weight that it is always cheaper to take two or more other edges.[1] We use two functions called `incomplete_prune` and `complete_prune` to this end.

In the incomplete pruning function, we consider two nodes k and l connected by an edge with weight $w(k,l)$. Then we try to find a shorter path through another node m connected to both k and l with edges weighted by $w(k,l)$ and $w(l,m)$. For each node k we check whether there are nodes l and m and edges with weights $w(k,m)$ and $w(m,l)$ such that $w(k,l) > w(k,m)+w(m,l)$.

As it is shown in Fig. 5 (a), there are two paths from the start point to the endpoint: (1) from node k through node l to node m and (2) from node k directly to node m. The length of path (1) is 50 and the cost of choosing the second path is equal to 40. Therefore, by removing the edge between nodes k and m, (see Fig. 5 (b)), we do not lose any shortest paths but improve the search performance. The code of this scenario is shown below.



(a) Before pruning (b) After pruning

Figure 5: Prune-incomplete function.

```
for k in g.nodes():
    for l in g.neighbors(k):
    # K<L is considered is for optimization
    if k < l:
        for m in g.neighbors(l):
            if g.has_edge(k,m) and
                g[k][l]['weight'] >
                g[k][m]['weight'] +
                g[m][l]['weight']:
                to_prune.add((k,l))
for u,v in to_prune:
    if g.has_edge(u,v):
       g.remove_edge(u,v)
```

The complete function likewise considers two nodes k and l. It uses the function `astar_path_length` from `networkd`, which returns the length of the shortest path between the nodes k and l by using the A* algorithm. If the weight of the edge between these two nodes $w(k,l)$ is strictly greater than the result of `astar_path_length`, the algorithm remove the edge (k,l) from E. Following code shows the complete function for pruning the redundant edges.

```
for k in g.nodes():
    for l in g.neighbors(k):
        if k < l and g[k][l]['weight'] >
            networkx.astar_path_length(g,k,l):
            to_prune.add((k,l))
for u,v in to_prune:
    if g.has_edge(u,v):
        g.remove_edge(u,v)
```

Table 2 shows routing times in seconds for a long route in Denmark when using different (combinations of) pruning functions. The edges pruned by using the complete function are exactly the same as the pruned edges by using the combined incomplete-complete function, which is reflected in the routing time. From the results in Table 2, we can conclude that the graph, which is created by using either the complete or combined pruning function, works best for routing, and the graph which have not use any pruning function works worst. The time of pruning for the incomplete function is almost the same as the time of pruning for incomplete-complete function, while the time of pruning for the complete function alone is the longest. Consequently, we use the combined function as it has optimal routing performance and a quite competitive pruning time.

Table 2: Routing with different pruning function for Denmark.

pruning type	pruned edges	routing time	pruning time
incomplete	41,001	0.161	17.57
complete	79,657	0.156	138.99
incomplete-complete	79,657	0.152	20.36
without both functions	0	0.449	0

In the next section, we explain our routing strategy, which is based on using the standard A* implementation of the `nextworkx` library for finding the shortest path in the graph.

3.3 The Use of Standard A* Implementations on the Graph

In this research, we use the standard A* implemented in `networkx`, an open-source python package for analyzing networks and graphs algorithms. The function `astar_path` gets the location of the start power tower, the location of the end power tower, the graph, and a distance function to compute the distance of any location to the end power tower. The result of `astar_path` is the shortest path between these two points. The code below shows how to use the `networkx` library for finding the shortest path between power towers.

[1]Note, that this is possible as the penalization of direct flights invalidates the triangle inequality.

```
import networkx as nx
path = nx.astar_path(g,start.tower,
        end.tower,heuristic=dist)
```

In the next section, we analyze Denmark as a use case for measuring the routing time when using the direct algorithm and the transformation algorithm.

4 EMPIRICAL EVALUATION (DENMARK)

This section is split into three subsections. In the first subsection, we evaluate the direct algorithm when using either no cache, the disk-based cache, or the memory-based cache file. In the second subsection, we evaluate the pre-filling cache file by either using the single-threaded or the multi-threaded approach. In the third subsection, we evaluate the transformation algorithm with a graph extracted from the memory-based cache for routing randomly selected power towers in Denmark.

4.1 Performance of the Direct Algorithm

In this subsection, we evaluate the performance of the direct algorithm for routing between two points in Odense (Denmark), which are *17.95* km from each other. We evaluate the three following configurations:

- **Direct Algorithm Without Any Caching:** Without a cache, the performance of our routing algorithm is very slow. Routing time takes *410* seconds.
- **Direct Algorithm With Disk-based Cache:** In this approach, we cache data in an initially empty disk file as described previously. This performs significantly better, reducing the routing time to *4.15* seconds.
- **Direct Algorithm With Memory-based Cache:** In this approach, we cache the data in a memory-based cache file. Routing by using this approach takes *3.01* seconds.

It is clear from the above results, that routing with the memory-based cache works faster than the other two approaches, as the queries to memory are faster than the queries to disk. Furthermore, performance without caching is totally unacceptable.

In the next subsection, we use multi-threading and the memory-based cache in order to incrase the performance of the pre-filling of the cache.

4.2 Single-threading and Multi-threading for Pre-filling of Cache with Disk-based and Memory-based Cache

As we have seen in the previous section, we can pre-fill the cache to increase routing performance by using a disk-based cash or the memory based-cash. We can also use multi-threading to speed up the process. In this section, we evaluate these options empirically by considering the country of Andorra as an example:

- **Single-threaded Pre-filling of the Cache with the Disk-based Cache:** This approach is very slow, as queries to disk are relatively slow. The pre-filling of the cache in this approach takes *516.47* seconds.
- **Single-threaded Pre-filling of the Cache with the Memory-based Cache:** In this approach, we use the memory-based cache in order to increase the cache performance. It works slightly faster than the previous approach but it is still slow. The pre-filling of the cache in this approach takes *350.19* seconds.
- **Multi-threaded Pre-filling of the Cache with the Disk-based Cache:** In this approach, we use multi-threading with the disk-based cache. Multi-threading provides multiple threads of execution concurrently which should lead to faster overall execution. The pre-filling of the cache in this approach takes *377.02* seconds, though, making it slower than the single-threaded version. The reason is, of course, that the locking mechanism prevents simultaneous updates to the disk cache.
- **Multi-threaded Pre-filling of the Cache with the Memory-based Cache:** In this approach, we use multi-threading with the memory-based cache. Pre-filling of the cache in this approach takes only *17.52* seconds.

From the above experiment, we can conclude that for pre-filling the cache, the first approach (single-threaded with disk-based cache) is the slowest one and the fourth approach (multi-threaded with the memory base-cache) is the fastest one.

4.3 Random Routing Performance of the Transformation Algorithm

The performance of the transformation algorithm is much better due to the extracted and pruned labelled weighted graph. Fig. 6 shows the outcome of using this algorithm for one of the longest possible routes in Denmark. The start power tower is located

at (57.4468, 10.0260) and the end one at (54.8196, 9.3314) for a distance of approx. 295 km. Routing between these two towers takes only 0.1587 seconds. Even when we use the graph without pruning with the same start and end locations it takes 0.374 second, which is still quite acceptable.

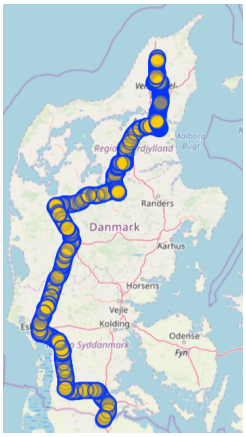


Figure 6: Routing through Denmark.

Table 3: Routing value for 1000 random samples.

Min	Max	AVG	Median	STD
4.92	238.99	73.32	65.31	53.85

Table 3 shows the minimum time (Min), the maximum time (Max), the average time (AVG), the median time (Median) and the standard deviation (STD) for 1,000 randomly select pairs of power towers in Denmark. Time in this table is in milliseconds rather than seconds.

Fig. 7 shows a box plot for these routing times of randomly selected pairs power towers in Denmark.

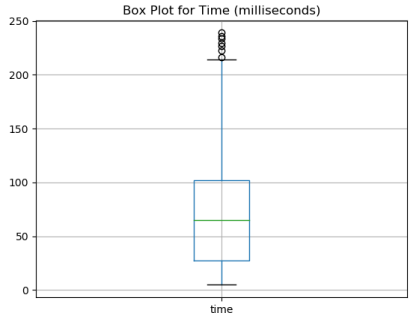


Figure 7: Box plot of 1000 routings for Denmark.

To summarize, the transformation algorithm is able to route between tower powers in Denmark in less than one second – and often in less than 100 milliseconds.

In the next subsection, we analyze France as a use case for measuring the routing time for a larger grid by using the transformation algorithm for 1,000 randomly selected routes.

5 EMPIRICAL EVALUATION (FRANCE)

In this section, we used the transformation algorithm for routing between randomly selected power towers in France. We measured the routing time for 1,000 random pairs of power towers.

Table 4: Routing value for 1000 random sample for France.

Min	Max	AVG	Median	STD
51.29	3076.86	591.09	480.34	435.14

Table 4 shows minimum time (Min), the maximum time (Max), the average time (AVG), the median time (Median) and the standard deviation (STD) in milliseconds. Fig. 8 shows a box plot for the routing times between these randomly select power towers in France.

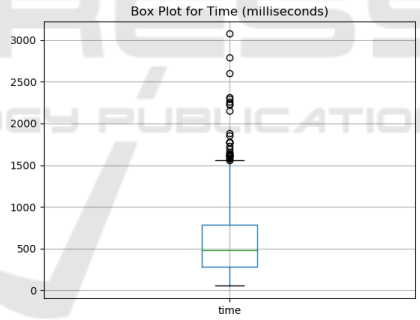


Figure 8: Box plox of 1000 routings for France.

To summarize, the performance of the transform algorithm is still very acceptable for larger power grids. The majority of routes takes less than one second.

In the next section, we analyze Europe as a use case measuring the searching performance of the transformation algorithm.

6 EMPIRICAL EVALUATION (EUROPE)

In this section, we measure the performance of the transformation algorithm for all European countries. In order to do that we need to follow steps bellow:

1. Pre-fill caches for all countries
2. Extract the graph from pre-filled caches for all countries
3. Merge graphs of all countries into a single graph
4. Use transformation algorithm for randomly selected pairs of power towers in Europe countries

Note in particular step 3), where in order to use the graph for routing by using the transformation algorithm, we have to merge the graphs of all countries into a single graph. In order to do that, we create a new graph containing all the edges from the individual country graphs. When building the country graphs, border-crossing power lines were kept in order to facilitate this process.

The code below shows how to merge graphs from different countries into a single graph.

```
for country in countries:
    for n1, n2, w in country.edges(data=True):
        g_merge.add_edge(n1,n2,**data)
```

As an example of using the transformation algorithm for routing in the European countries, we have set (37.1058271, -8.6962473) as the starting location and (55.4316748, 12.9769681) as the end location. Fig. 9 shows the outcome of routing algorithm computed in 28.38 seconds. The distance between the start location and the end location is 2,609.34 km. The total flying distance along the infrastructure is 6,951,307.18 km.

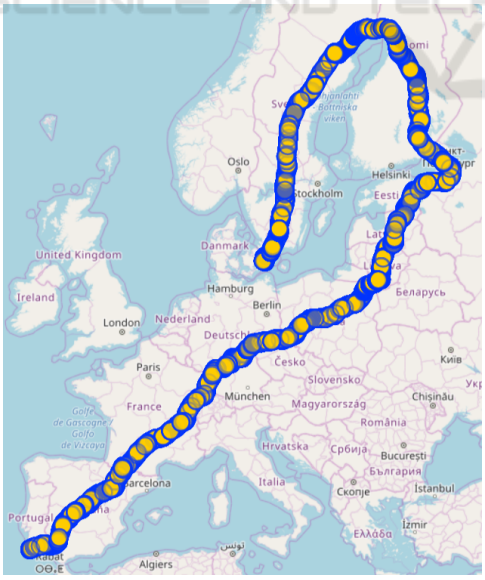


Figure 9: Routing through European countries.

7 CONCLUSIONS

In this paper, we have developed two routing algorithms for path planing of drone inspections along linear infrastructures: a direct algorithm and a transformation algorithm. We have shown that the transformation algorithm provides typical sub-second performance even on medium to long distances in large power grids such as the one of France.

More importantly, the more than satisfactory performance on short distances allows to use this routing algorithm as an ingredient in optimal mission planning, where routing can be used to determine the shortest distances between a number of inspection targets.

Future work could be to speed up the generation of the graphs by creating them directly from OpenStreetMap data. In principle, one could also go beyond A*-like algorithms, e.g. investigating the applicability of reach algorithms (Goldberg et al., 2006). With the level of performance demonstrated and the typically rather short distance in real-world use cases, this does not seem necessary, though.

8 OPEN-SOURCE AVAILABILITY FOR RELEVANCE AND REPRODUCIBILITY

In order to experiments to be reproducible, we packaged all results described in this paper as a Python package. The LiMiC (Linear-infrastructure Mission Control) package is available through The Python Package Index (PyPI) and can be installed either using the Package Installer for Python (PIP) by the command `pip install LiMiC` or by direct download from the PyPI: https://pypi.org/project/LiMiC/

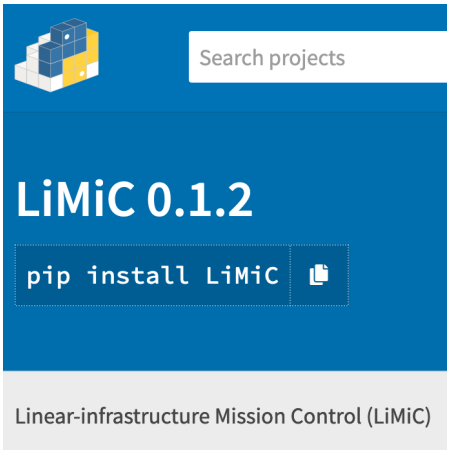


Figure 10: LiMiC on the PyPI.

The LiMiC package also also allows other researchers, drone companies, and drone enthusiasts to build upon the results described in this paper.

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https://drones4energy.dk/.

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