# OPTIMISED BUMBLEBEE PATHS AS SEARCH STRATEGY FOR AUTONOMOUS UNDERWATER VEHICLES

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**KEYWORDS**

Autonomous Underwater Vehicles, Path Planning Algorithms, Travelling Salesman Problem, Optimisation, k-opt

## ABSTRACT

In this paper, the concept of optimised bumblebee (BB) patterns as a search strategy for autonomous underwater vehicles (AUV) is presented. Here, an AUV is used to detect submarine groundwater discharge (SGD) in coastal areas. The optimisation of the BB paths is achieved utilising k-opt optimisation. In this research, 2-opt, 3-opt and 4-opt is used for the optimisation of the BB paths. It is shown using computer simulations that all three optimisation strategies are able to improve the search capabilities of the BB search strategy. The optimisation of the BB path shortens the length of the path to visit the waypoints generated. The saved energy can be used for exploring the search space in more detail, allowing the visit of waypoint the unoptimized BB was not able to reach. The median saved path length is 33.8 m, 43.5 m and 52.6 m for the 2-opt, 3-opt and 4-opt, respectively. The median error over 1,000 experiments of the not-optimised BB is 76.26, while the median error of the optimised BB are 71.63, 72.02 and 72.23 for the 2-opt, 3-opt and 4-opt, respectively.

## INTRODUCTION

The long-term goal of this research is to develop a flexible and low-cost autonomous multi-sensor platform for submarine exploration. Such a platform could be used for the localisation and investigation of submarine sources of interest like dumped waste, lost harmful cargo or submarine groundwater discharge (SGD) (Burnett et al. 2006). The term SGD covers any flow of water across the seabed regardless of the composition and the driving forces (Burnett et al. 2006; Moore 2010). Hence, SGD includes the discharge of fresh groundwater as well as the discharge of recirculating seawater (Figure 1). Due to the higher load of nutrients, SGD inflow can have an influence on the marine environment (Luijendijk et al. 2020).

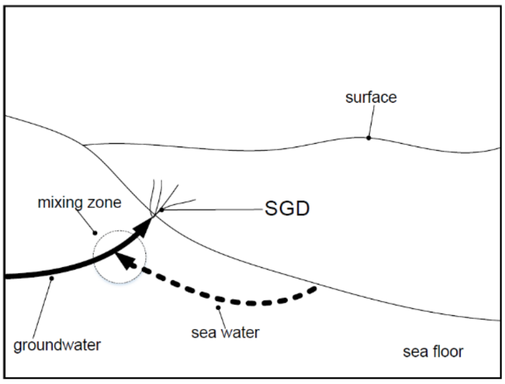


Figure 1: Submarine groundwater discharge (SGD) consisting of fresh groundwater and recirculating seawater

Different methods, such as seepage meters (Lee 1977; Taniguchi et al. 2003; Seibert et al. 2020), tracer studies

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(Burnett et al. 2006), remote sensing (Mallast and Siebert 2019), or seismic surveys (Smith et al. 2003; Stieglitz and Ridd 2000; Taniguchi et al. 2019), have been utilised for SGD investigation. More recently, small unmanned underwater vehicles (UUVs) were used as a tool for SGD site investigation (Tholen et al. 2021).

UUVs can either be remotely controlled by a human pilot over a tether, i.e. remotely operated vehicle (ROV) or, without a tether, by an algorithm running on an onboard computer, i.e. autonomous underwater vehicle (AUV) (Christ and Wernli 2011).

During their missions, AUVs usually follow a pre-defined path, for instance a series of different transects defined by waypoints (Wynn et al. 2014; Marouchos et al. 2015), or an adaptive sampling strategy (Hwang et al. 2019; Mo-Bjorkelund et al. 2020) to achieve a given goal. The search capabilities could be potentially improved by incorporating artificial intelligence (AI) into the strategy. Often, AI strategies, for instance particle swarm optimisation (PSO) (Kennedy and Eberhart 1995) or ant colony optimisation (ACO) (Dorigo et al. 2006; Nolle 2008), mimic the behaviour of social entities, like schools of fish, flocks of birds, or colonies of ants, and hence are population-based.

The bumblebee (BB) search strategy has been used as search strategy to guide a small swarm of AUVs during the search for SGD sites (Tholen et al. 2022). However, in this research, only a single AUV was used during the simulations.

### Bumblebee

The BB search strategy is inspired by bumblebee flight paths (Dukas and Real 1993; Philippides et al. 2013) and was developed by Hwang et al. (2020). The search strategy applies a combination of zigzag and double loops within the search space. In the first step, a specific number of waypoints is generated randomly and a path to visit all waypoints is computed. Upon arrival at a waypoint, the AUV undertakes a bow-tie shaped path with two loops. The radius of the loops *r* and the offset between the loops *O* are chosen by the operator prior to the search. The execution of the loops adds local exploitation capabilities to the search algorithm.

Due to the limited energy storage onboard of an AUV, a maximum travel distance for each AUV is defined. Therefore the maximum number of waypoints, utilising the given travel distance, are generated to maximize the search capabilities. All waypoints are chosen during a planning phase prior the search take place. During this planning phase, new waypoints are added iteratively to the paths until the expected path length is longer than the maximum travel distance of the AUV. The waypoint generation can be viewed as a travelling salesman problem (TSP) (Lawler 1995). Algorithm 1 shows pseudocode for the waypoint-planning algorithm.

Figure 2 shows an example trajectory of a single AUV utilising the BB algorithm as search strategy. It can be observed that the generated waypoints are spread over the whole search area, allowing the exploration of the entire area under investigation. However, the search strategy does not utilise the information gained during the search to adapt the search path to exploit promising regions in more detail.

Algorithm 1: Pseudocode for waypoint creation of the bumblebee (BB) algorithm

```
WP = generate two random position
max_dist_reached = false
while not max_dist_reached do
  distance = calc_travel_dist()
  if distance < max_distance do
    WP = [WP , random position]
  else
    max_dist_reached = true
  end if
end while

function dist = calc_travel_dist()
  N = number of WP
  dist = N*4*π*r+O
  current_point = startpoint
  open_list = WP
  for I = 1 : N do
    td = vector of distances between current_point and all elements of open_list
    n = index of min(td)
    if td(n) > threshold do
      dist = dist + td (n)
      current_point = open_list(n)
      delete open_list(n)
    else do
      %Drop WP, too near to other WP
      delete open_list(n)
    end if
  end for
end function
```

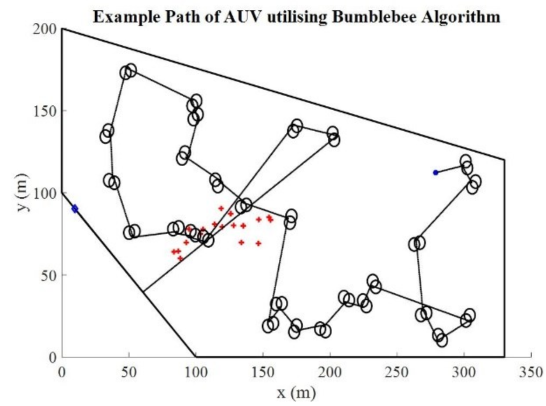


Figure 2: Example path of the BB search algorithm, start and end point of the autonomous underwater vehicle (AUV) are marked by the blue circle and diamond, respectively; Position of submarine groundwater discharges (SGDs) are marked by red crosses

During the generation of the waypoints, direct travelling in a straight line between two waypoints is assumed. However, due to self-localisation errors, the AUV is not travelling in a straight line. It rather produces zigzag paths resulting in a waste of energy between two waypoints. Therefore, not all waypoints generated can be visited (Tholen et al. 2022). Hence, in most cases, the BB strategy is not able to guide the AUV to investigate all parts of the search area, resulting in a poor search performance of the BB strategy, compared to other strategies (Tholen et al. 2022).

Optimising the path, i.e. find a shorter path to visit all waypoints, might be a suitable solution to tackle the problem described above. A shorter path will save energy which then can be used to visit more waypoints from the list of generated waypoints. This will increase the coverage of the search area and therefore potentially increase the search performance of the BB algorithm. The following research hypothesis will be addressed in this paper: "For an AUV, which utilises BB search strategy, optimising, i.e. minimizing, its path length can increase the search performance". A positive correlation between the saved path length and the performance of the search strategy is assumed.
Different approaches to optimise TSP problems, like ACO (Dorigo et al. 2006), simulated annealing (Linhares and Torreão 2011) or k-opt heuristic (Chandra et al. 1999) were proposed in the past.

**K-opt Optimisation**

In this research, k-opt optimisation was used, due to the simple implementation. Other optimisation strategies, for instance simulated annealing would require additional afford for parameter tuning. To answer the research questions of this paper a simple optimisation strategy is sufficient. During the optimisation process, $k$ points from the list of waypoints are randomly chosen. In the next step, all possible permutations of the $k$ points are calculated. For each of the permutations, the travel length for visiting all points is calculated. The permutation of the points is kept, if this calculated travel length is shorter than the travel length without the permutation. Otherwise, the permutation is rejected. The optimisation process is repeated $n$ times. Algorithm 2 shows pseudocode of the optimisation process described.

Algorithm 2: Pseudocode of the k-opt strategy used

```
for I = 1:n do
  k_WP = select k WP randomly
  perm_k = all permutations of k_WP
  for j = 1:k! do
    temp_W P= WP using perm_k(j)
    temp_tl = calculate travel length
with temp_WP
    if temp_tl < best_tl do
      best_tl = temp_tl
      WP = temp_WP
    end if
  end for
end for
```

It can be observed from Algorithm 2 that the computational costs of the optimisation process depend on the chosen values for $k$ and $n$. The number of optimisation steps can be calculated as follows:

$$S = n \cdot k!. \tag{1}$$

Where $S$ represents the total number of optimisation steps, $k$ represents the number of WP chosen for optimisation and $n$ is the number or repetitions.

**Simulation environment**

In this research, a dynamic simulation based on a real harbour environment was used. As shown in Figure 2, the dimensions of the simulated environment are 330 m x 200 m. The environment contains 20 SGDs. The number, position, strength and composition of the SGDs are randomly selected. The simulated environment used in this research is described in detail in Tholen et al. (2022).
To measure the success of the search strategy, the following error calculation was used:

$$E = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{\beta_i}\cdot \min\left(d_{1:t,i}\right). \tag{2}$$

Where $E$ represents the error of the search run, $n$ denotes the number of SGDs in the environment, $\beta$ represents the flowrate coefficient of the SGD and $d_{1:t,i}$ denotes the distances between the AUV and the SGD $i$ for all time steps $\{1 \dots t\}$ of the simulation.
This measure reflects which search strategy best fulfils the intended aims of the search. In this work, the environment contained $n$ SGDs with different flowrates. In the best case, the search strategy would be able to guide the AUV to visit all SGDs within the given maximum travel path length. Hence, the minimum distance between the AUV and all SGDs is used for fitness evaluation. In addition, the flowrate of the different SGDs is kept into account. That means it is more important to investigate SGDs with higher inflow, rather than visiting SGDs with lower inflow.

**EXPERIMENTS**

To answer the research question of this work, a set of 1,000 experiments was conducted. The number of experiments was chosen as a trade-off between computing time and number of results. In each experiment, different values of $k \in \{2,3,4\}$ were investigated. In each experiment, the optimisation process was repeated for $n$ = 1,000 times.
For a fair comparison, all four different options, i.e. not-optimised-BB, 2-opt-BB, 3-opt-BB and 4-opt-BB, were evaluated at the same time within the same simulated environment. Each search option is assigned to a single AUV. Here, in the first step of the setup, a set of waypoints is generated according to Algorithm 1.
The set of waypoints is directly used by the not-optimised-BB and used as starting point for the 2-opt-BB, 3-opt-BB and 4-opt-BB.
After the optimisation is finished, all four solutions are executed simultaneously within the same environment. The simulation is iteration based, while the time-lapse of each iteration step is 1 second. In each iteration, the four AUVs are moved and the performance, following equation (2) is updated. At the end of each experiment, the performance of the four options is stored for later use. This will allow for a fair comparison between the four different options.

For the experiments, the maximum travel length of the AUVs was set to 2,700 m. The radius *r* was set to 6 m and the offset between the circles was 3 m. The self-localisation of the AUV was error affected using a Gaussian error model with a standard deviation of 0.5 m. These values were chosen according to the findings presented in Tholen et al. (2022).

## RESULTS AND DISCUSSION

The length of the optimised paths should be shorter than the length of the not-optimised path. Figure 3 shows a histogram of the path length saved by the three optimised BB compared to the not-optimised BB. Statistical parameters for the different optimised BB are summarised in Table 1. It can be observed that the average amount of path length saved is positive correlated with the value chosen for *k*. Hence, the chosen k-opt optimisation strategy is able to optimise the path generated by the BB algorithm presented in Algorithm 1.

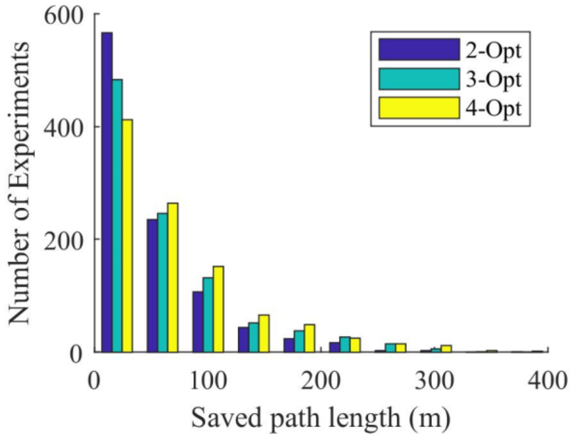


Figure 3: Histogram of path length saved by the three optimised BB compared to the not-optimised BB

Table 1: Summarised statistical parameters of the path length saved by the three optimised BB

| | Strategy | | |
|---|---|---|---|
| | 2-Opt | 3-Opt | 4-Opt |
| Median | 33.8 m | 43.5 m | 52.6 m |
| Mean | 49.3 m | 61.4 m | 70.4 m |
| Standard deviation | 52.8 m | 62.2 m | 67.5 m |
| Minimum | 0 m | 0 m | 0 m |
| Maximum | 402.0 m | 328.5 m | 402.0 m |

The length of the paths are calculated prior the search took place. Direct movement is assumed between the waypoints. However, as mentioned above, the movement of the AUV is affected by a self-localisation error of the AUV. Therefore, in most cases, the AUVs are not able to visit all waypoints generated before the energy of the AUV is consumed. Figure 4 shows a histogram summarising the percentage of remaining waypoints for the four different BBs. The remaining waypoints, are the waypoints that cannot be visited by the AUV due to energy restrictions. It can be seen from the figure that the optimisation process is capable of reducing the number of waypoints that the AUV was not able to visit.

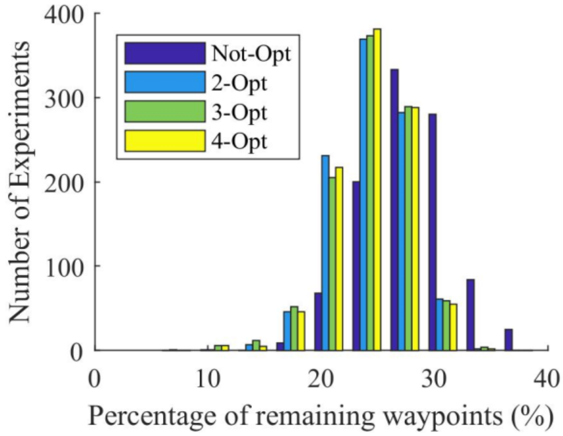


Figure 4: Histogram of the remaining waypoints for the not-optimised BB and the three optimised BB

Figure 5 shows the histogram of the error, calculated following equation (2). In Table 2 statistical parameters of the error scored by the different options are summarised. It can be seen from the figure and the table that all optimised versions of BB gave better results than the not-optimised BB. However, the results for all three optimised BB are in the same order of magnitude.

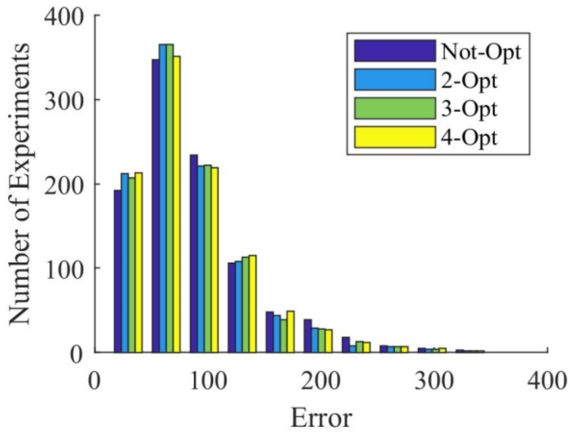


Figure 5: Histogram of error values for the not-optimised BB and the three optimised BB

Table 2: Summarised statistical parameters of the error for the not-optimised BB and the three optimised BB

| | Strategy | | | |
|---|---|---|---|---|
| | Not-Opt | 2-Opt | 3-Opt | 4-Opt |
| Median | 76.26 | 71.63 | 72.02 | 72.23 |
| Mean | 88.48 | 83.40 | 83.99 | 84.68 |
| Standard deviation | 52.23 | 48.20 | 48.74 | 49.76 |
| Minimum | 13.62 | 14.35 | 14.76 | 12.92 |
| Maximum | 346.61 | 333.95 | 348.53 | 346.93 |

The optimised BB used the same waypoints as the not-optimised BB. Therefore, the difference in the error for each experiment $\Delta E_i$ can be calculated as follows:

$$\Delta E_i = \frac{E_{not-opt,i} - E_{opt,i}}{E_{not-opt,i}} \cdot 100. \qquad (3)$$

Where $E_{opt,i}$ denotes the error value of the k-opt optimised BB and $E_{not-opt,i}$ denotes the error value of the not-optimised BB in the specific experiment $i$. Positive values for $\Delta E_i$ indicate a better result achieved by the optimised BB, while negative values indicate a worse result for the optimised BB compared to the not-optimised BB. Figure 6 shows the histogram of $\Delta E_i$ for all three optimised BB strategies investigated. Statistical parameters of $\Delta E_i$ are summarised in Table 3.

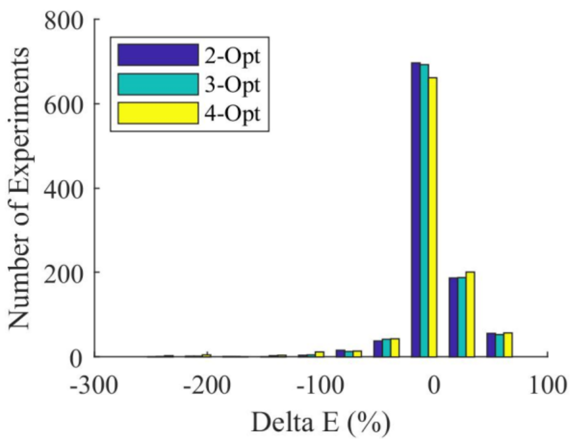


Figure 6: Histogram of $\Delta E_i$; positive values are representing a decrease in the error, i.e. improvement compared to not-optimised, while negative ones represent an increase respectively

Table 3: Summarised statistical parameters of $\Delta E_i$

| | Strategy | | |
|---|---|---|---|
| | 2-Opt | 3-Opt | 4-Opt |
| Median | 1.1 % | 1.0 % | 1.0 % |
| Mean | 2.2 % | 1.2 % | -0.14 % |
| Standard deviation | 24.4 % | 26.6 % | 32.5 % |
| Minimum | -219.2 % | -227.0 % | -258.2 % |
| Maximum | 74.3 % | 73.3 % | 74.5 % |
| Better | 590 | 550 | 561 |
| Worse | 410 | 450 | 439 |

It can be seen from the table that, based on the median, all three optimised BB performed better than the not optimised BB. However, in 41.0 %, 45.0 % and 43.9 % of the experiments, the performance of the 2-opt, 3-opt and 4-opt BB strategy is worse compared to the not optimised BB. A possible explanation for this worse performance is shown in Figure 7. In some cases, the optimisation process may change the order of the waypoints in such a way that the new path does not cross the area of the SGD, even if the not-optimised path did.

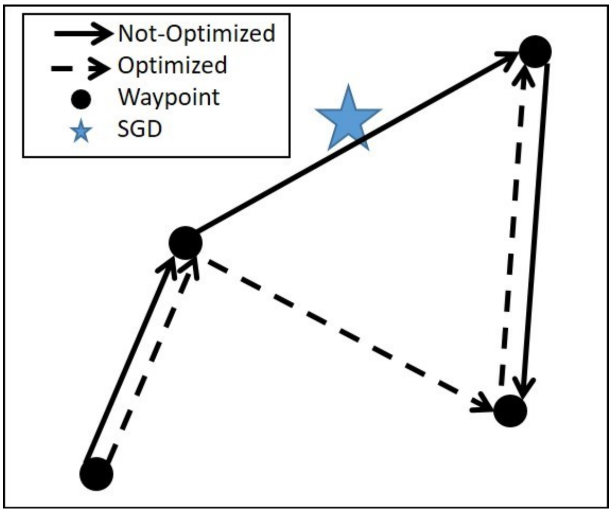


Figure 7: Possible explanation for the decrease in performance caused by optimisation; waypoints are marked by circles

If the postulated research hypothesis would be true, a positive correlation between $\Delta E_i$ and the saved path length would be expected. Figure 8 shows a scatter plot of $\Delta E_i$ over the saved path length for the three different optimised BBs. No positive correlation between the two variables can be observed for any of the optimised BB. In addition, in some experiments with a high saved path length, the achieved performance is bad compared to the performance of the not-optimised BB.

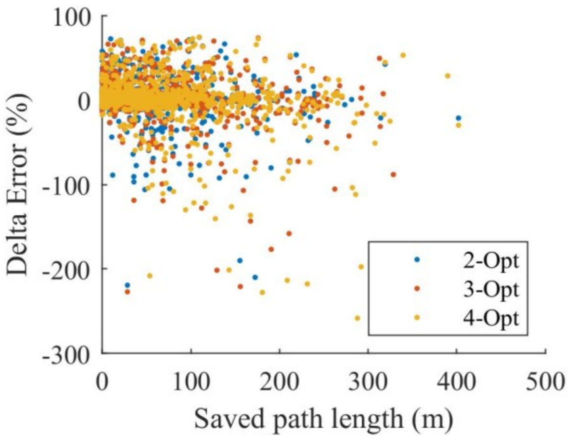


Figure 8: Scatter plot of $\Delta E_i$ over the saved path length

## CONCLUSIONS AND FUTURE WORK

In this research a simple optimisation strategy, i.e. the k-opt strategy, was used to improve the search performance of an AUV utilising the BB search strategy to search for SGDs. In this research, 2-opt, 3-opt and 4-opt were used. On average, all three optimised BB outperformed the not-optimised BB. However, the achieved reward of all three optimised BB was in the same order of magnitude. Therefore, the 2-opt strategy is the best option, due to the

much lower computational costs, compared to the 3-opt and 4-opt strategy.
Only in 56.7 % of all conducted experiments the optimised BB performed better than the not-optimised BB. Therefore, nearly in every second run, the optimised BB performed worse compared to the not-optimised BB. In the worst case, the error of the 4-opt optimised path was 258.2 % inferior to the not-optimised BB. Thus, optimising the path of the AUV does not guarantee an increasing performance of the search. Another possible solution to improve the performance of the BB search would be the incorporation of feedback, gained from the environment, to guide the search towards more promising regions of the search space.
In future research, different ways for the online adaptation of the list of waypoints, based on the current state of the search, will be evaluated.

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