Planning Sensing-Enabled Submarine Optical Networks under Cost and Coverage Constraints

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***Abstract*—We propose and evaluate a multi-route planning mechanism for subsea optical cables using optical sensing, formulated as a multi-objective optimization problem that balances deployment constraints while maximizing sensing coverage across monitored regions. It is assumed that the seabed is represented by a grid-matrix, and each node, along with its geospatial coordinates, is characterized by a set of properties such as seismic risk, seabed depth, etc. The Multi-Objective Minimum Cost Flow (MOMCF) mechanism is deployed to optimize sensing performance. The goal of Minimum Cost Flow approach is to find spatially disjoint candidate paths and evaluate their contribution to the optimal solution (cost vs sensing coverage trade-off). Additionally, a heuristic approach -the Multi-Objective Shortest Path-based Selection Mechanism (MOSP)- is implemented to resolve the polynomial execution time complexity of MOMCF. The simulations show that sufficient levels of sensing coverage can be achieved while respecting deployment costs constraints.**

***Index Terms*—route planning, sensing-enabled cables, submarine cables, distributed fiber optic sensing**

I. Introduction

Submarine telecommunications cables form the backbone of the global digital ecosystem, carrying the vast majority of international data traffic. With the rapid expansion of 5G/6G networks, cloud computing, and (Generative) AI, the submarine communication cables have grown by over 300% since 2010 [1], making their role even more critical.

Beyond connectivity, submarine cables are increasingly being repurposed from passive data pipes into active sensing systems. Distributed Fiber Optic Sensing (DFOS), through backscattering-based methods such as Distributed Acoustic Sensing (DAS) and Distributed Temperature Sensing (DTS), and Joint Communication and Sensing (JCAS) approaches using forward-propagating State of Polarization (SOP) analysis, transform the optical fiber itself into a large-scale, continuous sensor array. These technologies can sense and provide early warnings for earthquakes and tsunamis, while simultaneously monitor for accidental damage, vessel activity, and other security threats. In this way, submarine networks evolve into integrated real-time observatories that strengthen resilience, enhance maritime domain awareness, and improve global disaster preparedness.

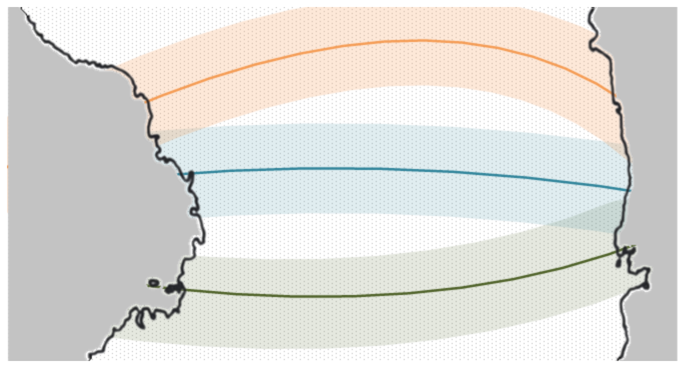

Fig. 1: Multiple paths to increase Sensing Coverage (J_C).

A key aspect of the subsea infrastructures is the cable route selection, also known as cable planning. Cable route planning has also been the subject of scientific studies [2] that usually apply graph-based processes, incorporating parameters in relation to the cost (e.g., cable installation or repair), reliability (e.g., seabed's characteristics, seismic activity) and performance, and employ multi-objective optimization to balance competing goals.

This paper investigates the route planning of submarine cables with the objective of enhancing the sensing capabilities of such deployments, through the coordinated deployment of multiple new cables and/or the utilization of existing ones (Fig. 1). Multiple-fiber sensing has been suggested on land for 3D strain measurement [3]. To the best of our knowledge, this is the first work considering cooperating submarine fibers so as to enhance event localization, introducing a novel dimension in route planning that has not been previously explored. This is also highly relevant given the rapid advancement of sensing technologies in submarine cables and the continuous global expansion of cable infrastructures.

II. Submarine optical cables sensing capabilities

The sensing capabilities of a submarine optical cable relate to the following aspects: (i) the effective sensing range around the fiber, which determines how far from the cable events can be detected; (ii) the sensitivity decay along the fiber, which

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limits the maximum distance at which events can be reliably sensed; and (iii) the range of detectable events, which may include environmental or geophysical phenomena.

Authors in [4] demonstrated that Distributed Acoustic Sensing (DAS) on an Arctic fiber optic cable can simultaneously detect, track, and identify diverse phenomena, including whales, ships, storms, and earthquakes. Fiber-optic sensing can detect larger earthquakes over longer distances. Moderate events (M_w 3.0–4.0) are detectable up to 90 km [5], larger quakes (M_w 6.6) up to 2,300 km [6], and very large earthquakes (M_w 8.2) beyond 13,800 km [7]. Distributed Fiber Optic Sensing (DFOS) technologies, typically operate over fiber distances, ranging from tens of kilometers without amplification to up to a few hundred kilometers with advanced amplification [8]. For example, when using amplification, commercial DAS systems commonly reach $>$ 100 km to 150 km, with research systems demonstrating functionality over distances as long as 300 km [8]. In this work, we primarily focus on DFOS systems, under the assumption that the selected cables connect two shores; however, in practice, DFOS cables may also terminate offshore. Also, our approach can be readily extended to Joint Communication and Sensing (JCAS) -based systems, taking into account constraints such as the locations of the landing stations and the more limited sensing range of JCAS approaches.

III. Multiple Routes Planning Mechanisms and Sensing Coverage Metric

A. Multi-Objective Minimum Cost Flow-based Selection Mechanism (MOMCF)

We implemented a multi-criteria, multi-disjoint-path routes planning mechanism for optimizing the collective sensing capabilities of deployed subsea cables. The seabed is modeled as a two-dimensional grid graph $G = (V, E)$ of size $N \times N$, where each node $v_i \in V$ is associated with a cost vector $C_i = p_{a_i}, p_{b_i}, \ldots$ describing the characteristics of that specific location in terms of various properties, such as seabed depth, seismic activity, or fishing hazards. Graph edges represent spatial proximity between nodes, under the assumption of equal distance between neighboring grid points. Such matrices can be derived from geospatial or bathymetric datasets, typically obtained from marine surveys, satellite altimetry, or public seabed mapping services (e.g., GEBCO, EMODnet, or NOAA). Each matrix cell corresponds to a spatial sampling point, and the associated property values (e.g., depth, sediment type, or seismic activity) can be extracted, interpolated, or normalized to form the cost grid used in our model.

The path planning process follows a two-stage sequential optimization approach, as presented in Algorithm 1. For simplicity, in the remainder of our study, we assume that each node i is characterized by a single property value z_i, while additional metrics (e.g., hop count / cost and sensing coverage) are considered in the second phase of the path planning process.

Algorithm 1 Multi-Objective Minimum Cost Flow -based Selection Mechanism (MOMCF)

Require: Graph $G(V, E)$; number of desired paths K; property weights λ_j; weighting coefficient α; maximum hop budget $H_{\max}$
Ensure: Optimal subset of routes $\mathbf{S}$ and corresponding score $BestScore$

procedure Phase 1: Candidate Path Generation (MOMCF)
  Compute scalar cost for each node v_i using weighted sum of properties: $C_i^{\text{scalar}} = \sum \lambda_j c_{i,j}$
  Solve a Minimum Cost Flow problem to obtain K node-disjoint paths
  $\mathbf{P} \leftarrow \{p_1, p_2, \ldots, p_K\}$ ▷ Set of K candidate paths
end procedure
procedure Phase 2: Subset Selection via Exhaustive Search
  $BestScore \leftarrow -\infty$, $\mathbf{S} \leftarrow \emptyset$
  for each subset $\mathbf{S}' \subseteq \mathbf{P}$ **do**
    Compute coverage $J_C(\mathbf{S}')$ and total hops $H_C(\mathbf{S}')$
    if $H_C(\mathbf{S}') > H_{\max}$ **then**
      continue
    end if
    $Score \leftarrow \max_{\mathbf{S}' \subseteq \mathbf{P}} (\alpha \cdot J_C(\mathbf{S}') - (1-\alpha) \cdot H_C(\mathbf{S}'))$
    if $Score > BestScore$ **then**
      $BestScore \leftarrow Score$
      $\mathbf{S} \leftarrow \mathbf{S}'$
    end if
  end for
  return $\mathbf{S}, BestScore$
end procedure

The first step computes an initial set of K node-disjoint paths by modeling the grid G as a Minimum Cost Flow (MCF) network. This involves introducing a super-source (s), connected to all nodes in the starting column (left shore), and a super-destination (t), connected from all nodes in the ending column (right shore), to enforce a total flow of K. Every intermediate grid node v_i is split into two, with the connecting edge assigned a capacity of 1 (for disjointness) and a cost equal to the node's property value (z_i). Solving the MCF problem finds the K paths that satisfy the flow demand while inherently minimizing the collective property cost (C_{Prop}), which is the sum of the property values z_i of the unique nodes visited across all paths: $\min_P C_{Prop}(P) = \min_P \sum_{v_i \in \bigcup_{j=1}^{K} S_j} z_i$. This ensures for example that nodes with high seismic activity are avoided.

The second step selects an optimal subset of paths, $S' \subseteq P$, by maximizing a utility function $J(S')$ that trades off sensing coverage against hop count (corresponding to physical length and associated cost). The Sensing Coverage Metric (J_C), defined as the percentage of grid nodes either on or adjacent to a path or paths, indicating the area where sensing of events is possible. The objective function is: $\max_{S' \subseteq P} J(S') =$

$\max_{S' \subseteq P} (\alpha \cdot J_C(S') - (1-\alpha) \cdot H_C(S'))$. Here, α is the weight for the Sensing Coverage Metric (J_C), and H_C is the total hop count of the selected paths. The optimal subset S' is determined by a search over all possible combinations (subsets) of the initial K paths. Applying domination relations can reduce the number of initial paths, simplifying the subsequent subset enumeration.

The Sensing Coverage Metric J_C is a quantifiable measure of the area (in terms of nodes) of the grid adequately covered by the sensing capabilities of the selected routes S'. This metric is highly dependent on the sensing target, e.g. earthquake, vessel etc and the respective utilized technology capabilities. Also, both greenfield and brownfield design approaches should be considered assuming that the J_C is calculated only based on newly deployed fiber or also taking into account the sensing capabilities of existing infrastructure.

This two-step approach allows the identification of an optimal solution S'. However, while the execution time is relatively short for the small matrices used in this study, applying this method to larger seabed matrices or requiring a significantly larger set of initial disjoint paths (K) would result in prohibitively high execution times. Applying domination relations can reduce the number of initial paths, simplifying the subsequent subset enumeration. Consequently, while the execution time is very fast for the small matrices used in this study, applying this method to very large seabed matrices or requiring a much larger set of initial disjoint paths (K) would result in a prohibitively large execution time. However, the computational demand of the first step increases based on the size of the seabed matrix, while the demand of the send step increases very rapidly (exponentially) as the initial number of paths (K) grows. To overcome such issues, a heuristic mechanism is proposed in the next subsection.

B. Multi-Objective Shortest Path-based Selection Mechanism (MOSP)

The proposed heuristic approach called Multi-Objective Shortest Path-based Selection Mechanism (MOSP) is again composed by two phases, and is presented in Algorithm 2. In Phase 1, the Iterative Disjoint Non-Dominated Path Generation is performed. This process consists of three steps. Initially, the identification of possible paths that optimize multiple, potentially conflicting metrics (e.g., depth, risk, and hop count) takes place. Each path is evaluated using a vector-valued cost that aggregates node-level attributes through appropriate operators. Next, from the set of all possible paths, only non-dominated (Pareto-optimal) ones are retained, significantly reducing the search space. Among these, a scalar objective function is applied to select the most suitable path for the current iteration. Finally, to enforce disjointness and encourage diversity, the nodes of the selected path are penalized before the next iteration, steering subsequent searches toward alternative regions of the graph. This path generation process continues until no further paths can be identified, yielding a set of mutually disjoint, non-dominated candidate routes.

Algorithm 2 Multi-Objective Shortest Path -based Selection Mechanism (MOSP)

Require: Graph G, Multi-cost Link Data C_i, Max Total Hops $H_{\max}$
Output: Final Selected Routes $\mathbf{S}$

procedure PHASE 1: ITERATIVE DISJOINT PATH GENERATION
  Initialize Candidate Paths $\mathbf{P} \leftarrow \emptyset$
  while Termination condition not met (e.g., target paths reached or source-destination disconnect) **do**
    Compute Multi-dimensional Cost Vector $V(p)$ for all paths using MOSP.
    Generate Pareto-Optimal Set P_{n-d} using Domination Relations.
    Select $\mathbf{p}^*$ from P_{n-d} by minimizing a combined objective function f.
    Apply Cost Penalty to nodes/links of p^*.
    Add p^* to the Candidate Paths Set $\mathbf{P}$.
  end while
end procedure

procedure PHASE 2: ITERATIVE GREEDY FINAL SELECTION
  Initialize Final Routes $\mathbf{S} \leftarrow \emptyset$, Total Hops $H \leftarrow 0$
  while $\mathbf{P} \neq \emptyset$ **and** $H < H_{\max}$ **do**
    for each path p in $\mathbf{P}$ **do**
      Compute Score based on the Utility Function:

$$\text{Score}(p) = \alpha \cdot \Delta J_C(p) - (1-\alpha) \cdot \Delta H_C(p)$$

    end for
    Select best path $p^* = \arg\max \text{Score}(p)$
    if Score(p^*) is positive (or meets utility threshold) **then**
      Add p^* to $\mathbf{S}$
      $H \leftarrow H + \text{hop}(p^*)$
      Remove p^* from $\mathbf{P}$
    else
      break (Stop selection)
    end if
  end while
  Return $\mathbf{S}$
end procedure

In Phase 2, the previously generated candidate set is refined to determine the final subset of routes. Each candidate path is evaluated according to a utility function that balances marginal sensing coverage gains against incremental path cost, controlled by a tunable trade-off parameter. The algorithm greedily selects the path that maximizes this utility, adds it to the final solution set, and removes it from further consideration. This iterative process continues until either all candidates are exhausted or a global constraint on total hop count is reached. By operating on a reduced, high-quality

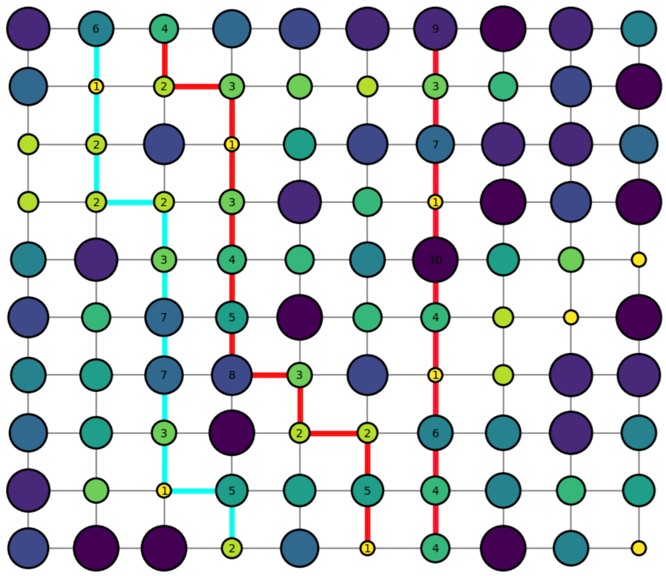


Fig. 2: Three routes are selected in a 10×10 nodes (with different property values, e.g., seismic activity) seabed matrix, which maximize Sensing Coverage (72%), with a minimum total routes' cost (as measured by hop count).

candidate pool, this phase efficiently constructs a final route set that achieves an effective compromise between coverage performance and resource expenditure.

IV. Evaluation

We performed a series of simulation experiments in order to evaluate the characteristics of the selected optimal routes under various conditions. Figure 2 illustrates a small seabed matrix 10×10, where each node's size depends on its assigned property value (e.g., seismic activity) and a number of routes have been identified (from top shore, to bottom shore) to maximize Sensing Coverage (72%) while minimizing their cost (as measured by hop count).

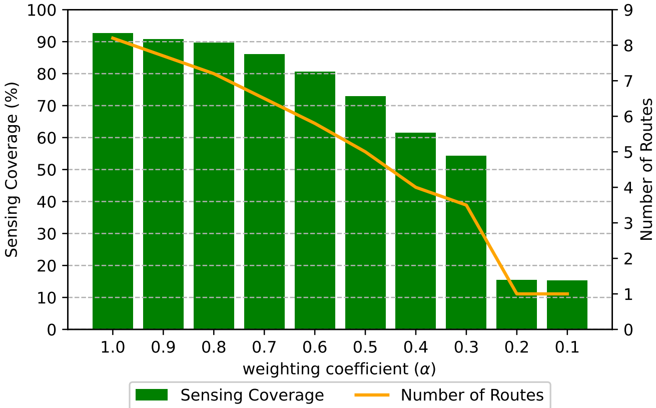
The experimental setup employed a seabed matrix represented as a 20×20 grid graph, where each node was assigned a property value $z_i \in [1, 10]$ (e.g., related to seismic or fishing activity). These values indicate the relative suitability of each region for cable deployment, where higher values correspond to areas that should ideally be avoided. Multiple property layers can also be incorporated to account for diverse environmental or operational constraints. The initial path generation stage was configured to identify up to $K = 10$ node-disjoint routes. Increasing the number of paths beyond this value significantly raised computational complexity, while using fewer paths tended to yield suboptimal or overly constrained solutions.

Initially, we conducted a sensitivity analysis by systematically varying the weights in the objective utility function (J). The coverage weight (α) was decreased from 1 (prioritizing coverage) down to 0.1 (prioritizing cost/shorter paths). This explored ten distinct scenarios, transitioning from highly coverage-driven to highly cost-driven solutions. The analysis focused on four Key Performance Indicators (KPIs), averaged across five randomized runs for the final optimal path subset (S'): the Average Group Size (number of selected routes), the Average Sensing Coverage Percentage (J_C), the Average Hop Count per Route (average physical length), and the Average Total Property Cost (C_{Prop}). Figure 3.a illustrates the results from this initial evaluation. We observed that as α decreases the sensing coverage decreases from 90% to 10%, while fewer route are also selected in order to decrease the cost of the designed infrastructure. The Average Hop Count per Route (average physical length), and the Average Total Property Cost (C_{Prop}) are also reduced in a similar manner. Next, we performed a number of experiments assuming that some nodes are already covered in terms of sensing from other, e.g., already established routes, and evaluated how this affects the new routes identified while altering the percentage of pre-covered nodes (Figure 3.b). We observed that as this percentage increases, the number of new routes found decreases along with the percentage of nodes covered by new routes, while the total percentage of covered nodes (from new and existing routes) remains relatively similar, stabilizing near an asymptotic maximum. This stability indicates that the optimization, constrained by the fixed cost-sensitive weights ($\alpha = 0.8$), has reached its maximum economic coverage efficiency. The optimizer rejects adding new, longer paths because the marginal cost in hops ($(1 - a) \cdot \mathrm{H}$) required to sense the few remaining, hard-to-reach nodes outweighs the marginal gain in weighted coverage ($\alpha \cdot \text{Coverage}$). This finding is critical for network planning, guiding decisions on where physical deployment efforts should be refocused or where alternative, non-path-based sensing solutions should be considered (e.g., adding a dedicated seismometer).

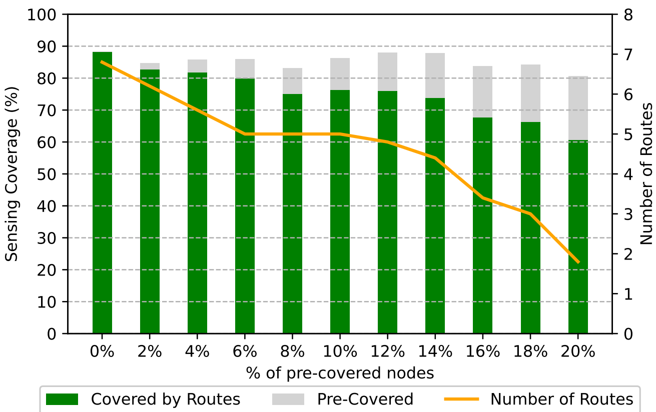
Next, we examined the performance of the heuristic Multi-Objective Shortest Path–based Selection Mechanism (MOSP) in comparison with the optimal Multi-Objective Minimum Cost Flow–based Selection Mechanism (MOMCF). As shown in Figure 4.a, using a 20×20 seabed grid and varying the percentage of pre-covered nodes, the MOSP heuristic attains sensing coverage levels that are close to those achieved by the optimal MOMCF solution. Figure 4.b further illustrates the sensing coverage and execution time of MOSP as the grid size increases. The results indicate that larger matrices negatively impact MOSP's ability to identify highly covering path sets ($\mathbf{S}$), while the computational time grows substantially, reaching several minutes. This observed degradation highlights the need for improved scalability, motivating further investigation into alternative approaches, such as clustering-based methods, which aggregate the original grid and subsequently enables the application of optimal solution techniques.

V. Conclusions

We proposed a framework for multi-objective, multi-route planning of sensing-enabled submarine cables that integrates environmental characteristics, installation costs, and sensing performance. This paper extends the conventional subsea route

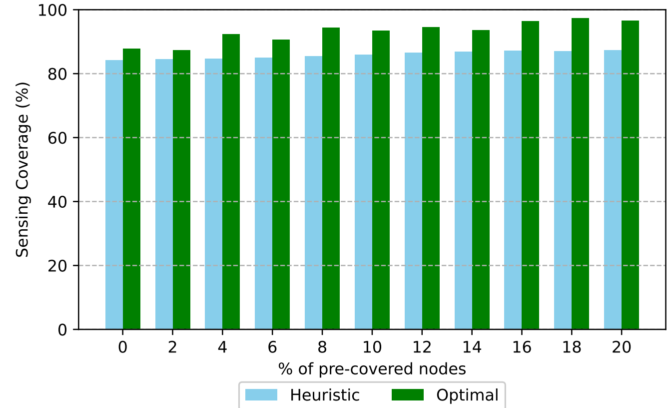


(a)

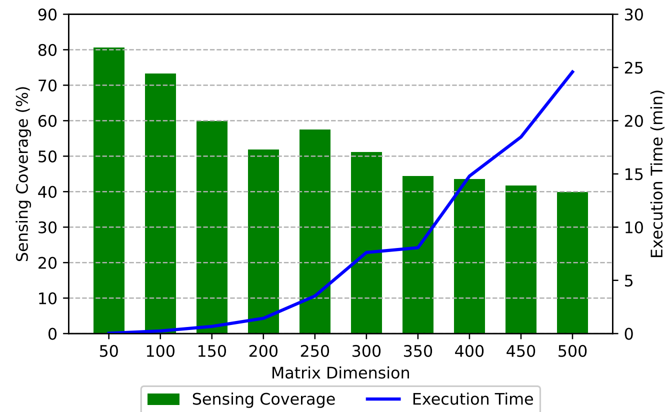


(b)

Fig. 3: The sensing coverage and the number of routes selected, varying: (a) the weighting coefficient α in the objective function (J), (b) the percentage of sensing pre-covered nodes.



(a)



(b)

Fig. 4: (a) The Sensing Coverage achieved with the optimal MOMCF and the heuristic MOSP varying the percentage of pre-covered nodes. (b) The Sensing Coverage and the execution time of the heuristic MOSP increasing the seabed grid matrix size.

optimization by exploiting combining the communication and sensing capabilities of optical infrastructures. To this end, two algorithms were developed and evaluated. The Multi-Objective Minimum Cost Flow–based Selection Mechanism (MOMCF) yields globally optimal solutions within the generated candidate set of paths, while the Multi-Objective Shortest Path–based Selection Mechanism (MOSP) provides a scalable heuristic alternative with near-optimal performance and substantially lower computational complexity. The simulation results indicate that both algorithms can achieve desirable trade-offs between sensing coverage and deployment/operational constraints.

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