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A Cost-effective, Environmentally-Aware Undersea Infrastructure to Enhance Community Resilience to Tsunamis

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Abstract

The focus of this paper is on mitigating the impact of near-field tsunami detection on humans and the environment. We propose a hybrid network infrastructure that combines an undersea sensor network with fiber optic cable for cost effective, timely, and reliable near-field tsunami detection. We first formulate a cost minimization problem for near-field tsunami detection. To capture important characteristics of the environment, the optimization model incorporates into its formalization important sea environment factors and a realistic acoustic propagation model. A heuristic approach is developed to derive a near-optimal solution to the original cost minimization problem. To demonstrate the viability of the proposed model, a case study, focused on Padang City is used, and a comparative analysis of different network configurations, using different design parameters and cost scenarios is performed. Three different cost functions, namely linear, power-law, and logarithmic, are used in the analysis. The results show that the heuristic computes efficient network configurations when a solution exists, for the linear, logarithmic, and power-law cost functions. However, further assessment should be made on the results to anticipate a local maximum that may exist in the cost function.

Keywords : *Near-field Tsunami, Undersea sensor, Fiber Optic cable, Cost, Timeliness, Reliability, Optimization, Heuristic*

1 Introduction

A tsunami consists of a series of sea waves generated by an ocean floor disturbance due to earthquake, underwater landslide, or large volcanic eruptions. These waves which can reach heights of tens of meters may cause high casualties, massive destruction, and large financial losses. The recurring failure of communities to assess, monitor and respond effectively to tsunamis underscores the discrepancy between current forms of organizational planning and actual capacity of individuals and organizations to act collectively in response to tsunami occurrences. Preparing for tsunamis has traditionally been the responsibility of public agencies. The recent 2009 Padang earthquake demonstrated that effective planning and preparedness for such events cannot be achieved by any single agency or jurisdiction. Instead, managing tsunami risk becomes the shared responsibility of all actors in the community.

An important aspect to improve community resilience is the availability of cost-effective and reliable interactive infrastructure for tsunami alert notification and continuous information dissemination among the

different stakeholders, prior to, during, and after a tsunami occurs. The availability of such an infrastructure is especially critical to manage effectively extreme events such as near-field tsunamis, which occur with relative infrequency in any one location, but cause significant damages when they do occur. Such information infrastructure allows the community to recognize risk and take informed action in a timely, responsible and collaborative ways.

The focus of this paper is on the development of a cost-effective, undersea infrastructure to enhance community resilience to near-field tsunamis. The proposed infrastructure, when integrated with onshore social media for information exchange, such as Twitter or opportunistic networks, will enable collective, tsunami awareness and support self-organizing action on a community-wide scale. To achieve this objective, we first develop an environment-aware optimization framework, including models that capture accurately the propagation of acoustic channels and reflect closely the characteristics of underwater environments. We then cast the cost-effective, environment-aware infrastructure problem as an optimization problem. Finding an optimal solution for this problem, however, requires computational resources far beyond what is practically available. Instead, we propose an approximation algorithm to derive a near-optimal solution for a reliable hybrid infrastructure, composed of an optic fiber cable augmented with acoustic underwater sensors, which meets the real-time requirement of a near-field tsunami detection system.

The remaining sections of the paper are organized as follows: Section 2 provides relevant background and presents the methodology used to derive the hybrid, undersea infrastructure. Section 3 introduces the basic technology of the proposed infrastructure and describes its topology and communication requirements. Section 4 discusses the formalization of the infrastructure problem as an optimization problem and derives its cost, reliability and delay characteristics. A heuristic approach to derive a near-optimal solution to the complex optimization problem is discussed in Section 5. A case study to explore the feasibility of the proposed approach to Padang City is presented, including the analysis of the results for different scenarios and parameter values.

2 Background and Methodology

Based on its vicinity to the coast, tsunamis can be classified into three groups, namely *local* or *near-field*, *regional*, and *distant* [1][2]. Coastal areas, located within 100 km from where a tsunami originates, may be subject to near-field tsunami threats. This category of tsunamis can reach the neighboring coastal areas within less than one hour after they occur. A regional tsunami generally occurs within a 1000 kilometers from the coast and travels between one to three hours before it hits the land. Lastly, a distant tsunami travels more than three hours before it reaches the land. The focus of this paper is on near-field tsunamis that present a severe threat to coastal communities, given the short travel time. The study in [3] reveals that 87% of tsunamigenic sources are located closer than 100 km from the coast in the Pacific

region. Taking into consideration these facts, an infrastructure for early detection requires stringent real-timeliness and reliability to mitigate the destructive impact of near-field tsunamis.

Several systems have been developed to detect and mitigate the impact of tsunamis. NOAA has developed the Deep-ocean Assessment and Reporting of Tsunamis (DART) system for tsunami detection [4]. DART consists of a sea floor bottom pressure recorder and a moored surface buoy. An acoustic link connects the recorder to the buoy for real time communication of temperature and pressure data. Then, the buoy sends the data to the land station through satellite communication. A different approach is described in [5], where the authors propose the use of a global positioning system technology to provide high resolution of geospatial data, combined with reasonable epicenter scenarios to provide spatial hazard maps.

The above systems have potential to detect tsunamis accurately and improve the community's emergency response preparedness. These systems, however, present multiple challenges, ranging from high acquisition cost to difficulty in deploying and maintaining them. The DART system, typically deployed in a deep ocean, is primarily designed to detect far-field, rather than near-field tsunamis. Severe weather conditions and storms may bring down many buoys, making annual servicing of the infrastructure both difficult and costly[6]. In addition to damage caused by natural calamities, buoy-based systems are vulnerable to vandalism, particularly in marine waters that are favorable to fishing [7]. These challenges limit considerably the use of these tsunami detection systems in third world countries, where the cost of deployment and maintenance is of a great concern.

To address these challenges, this paper proposes a buoyless, hybrid infrastructure, composed of undersea sensors and fiber optic cable, for near-field tsunami detection. The non-reliance on buoys is an attractive feature of the proposed infrastructure, as it reduces the propensity to vandalism. Several other factors, however, must be taken into consideration to reduce cost and achieve stringent real-time alert delivery requirements. Fiber optic cable provides high reliability and achieves fast data transmission, but the underwater deployment of optic fiber may entail prohibitively high cost. In contrast to fiber optics, the acquisition and deployment of undersea sensors is relatively cheap. Communication between underwater sensors, however, faces poor acoustic channel quality, which limits considerably transmission reliability [8]. Furthermore, communication between adjacent sensors exhibits high latency, making on-time delivery of tsunami alerts a challenge. Battery life may also become a concern, especially under heavy usage.

Integrating the two communications technologies of underwater sensors and fiber optic cable into a feasible solution that meets the reliability and real-time requirements of early near-field tsunami detection requires exploring a number of tradeoffs between cost, reliability, and timeliness. To do so, we propose an optimization model that captures the main characteristics of acoustic channel and undersea environment.

Undersea sensor networks mainly utilize acoustic channels as the viable media for communication. The sea environment has a significant impact on the sensor communications. Although acoustic technology achieves communication over longer ranges than radio waves, the latency of acoustic

channels is high, and the signal quality is susceptible to degradation due to environmental changes. To take into consideration the different characteristics of underwater communication, the optimization framework incorporates elaborate acoustic communication models, to capture accurately the dynamics of the acoustic channel. It also includes important factors that impact undersea communications to model a realistic operating environment. A bellhop acoustic propagation model is used to calculate acoustic transmission loss and acoustic propagation time. To model accurately the sea environment, three factors are considered, namely sea floor profile, undersea sound speed profile and sea ambient noise. The first two factors are obtained from measurement data, while the third is computed based on the Wenz curve[10]. The resulting optimization problem is computationally expensive to solve. To find a near-optimal solution of this complex problem, a heuristic approach is used.

Figure 1: Location of interest for optimization model case study

To demonstrate the feasibility of the proposed heuristic, a case study focused on designing a near-field tsunami detection system for a coastal region, where near field tsunami threats are imminent, is used. The area of interest covers Padang city, West Sumatera, Indonesia, depicted in Figure 1. According to studies in [5][11], Padang city is vulnerable to near-field tsunamis. It is estimated that it only takes about 30 minutes for a near-field tsunami, originating at an epicenter in, to reach the coast of Padang.

3 System Description

Figure 2 below illustrates the proposed hybrid network for near field tsunami detection. It comprises a line of undersea sensors augmented by fiber optic as the last communication link to the shore. Epicenter represents the region from where tsunami is likely to occur. Two distinct types of sensor nodes, a pressure sensor node and relay sensor nodes, are used in the deployment of the infrastructure. The pressure sensor node is composed of two modules with distinct functions: a pressure sensing module and an acoustic communication module. A relay sensor node contains only an acoustic communication model. The main

role of relay sensors is to facilitate the transmission of pressure data from the epicenter to the onshore control station, across multihop acoustic links.

Figure 2 : Near-field Tsunami Detection Topology and Basic Components

The pressure sensor node, located furthest from the coast, serves as the tsunami sensing node. Its main responsibility is to record the seafloor pressure and transmit the recoded data to the neighboring relay sensor node. The pressure sensor data packets are then exchanged between adjacent relay nodes and travel across a path of multihop acoustic links and a fiber optic link before they reach the control station ashore.

To detect a tsunami, the pressure sensor continuously reads and monitors the sea water column pressure changes caused by the tsunami waves passing over it. In the absence of any event, the pressure sensor collects and transmits pressure readings and temperature at regular intervals of time. Upon the detection of an event, however, the pressure sensor increases its transmission rate until no further events are detected. The control station receives the transmitted data, assesses it, and forwards the tsunami detection information to the designated agent.

In response to a near-field tsunami threat, a set of actions must be undertaken prior to the tsunami landing onshore. Consequently, the tsunami detection information must arrive at the control station in a timely fashion. This timeliness requirement is defined as the amount of elapsed time, measured from the time the data arrive at the control station reliably to the time the tsunami hits the coastal area. This time window is deemed sufficient to assess the tsunami threat and issue a subsequent alert for disaster managers and for the threatened community to conduct the planned evacuation actions.

It is worth noting that the timeliness requirement can be affected by the reliability of the transmission link between adjacent sensor nodes of the network infrastructure. A data packet received in error by the control station must be retransmitted. Packet retransmission increases the data delivery time and may result in the violation of the timeliness requirement. To achieve data delivery within the timeliness time window, transmission links, along the path from the pressure sensor to the control station, must achieve reliable data transfer with a probability that exceeds a specified threshold. We refer to this property of the network infrastructure as the reliability constraint. Since the reliability of the fiber optic link is very high, the focus will be on the reliability of the acoustic links.

The reliability of acoustic links depends on the distance between adjacent sensor nodes of the network. To meet the specified reliability threshold, the distance between pairs of undersea sensors should be such that the acoustic wave remains strong enough, even after suffering loss, to be interpreted correctly by the receiver. In addition to acoustic loss due to propagation, sea ambient noise also contributes to the degradation of the acoustic signal quality at the receiving node. Consequently, accurate estimation of the acoustic transmission loss and the loss caused by ambient noise is critical for the optimization framework to model correctly the reliability of the proposed infrastructure.

4 Optimization Model

The main objective of the optimization model is to minimize the infrastructure deployment cost, while satisfying the timeliness and reliability constraints. The infrastructure optimization problem can be formulated as follows:

$$\text{Minimize } C_{Tot} = C_F(L) + C_S(N_h)$$

Subject to:

$$T_{Warn}(L, \mathbf{D}, N_h) \geq \theta_T \quad (1)$$

$$R_i(L, d_i) \geq \theta_R, \quad 1 \leq i \leq N_h \quad (2)$$

$$L = \Delta - \sum_{i=1}^{N_h} d_i \geq L_{min} \quad (3)$$

$$\mathbf{D} = \{d_i | d_i \geq d_{min}\} \quad 1 \leq i \leq N_h \quad (4)$$

- The terms C_{Tot} , C_F and C_S denote the total deployment cost, the fiber optic deployment cost, and the undersea sensor network deployment cost, respectively.
- The parameter, Δ , represents the distance between the pressure sensor node and the location of the control station.
- The parameter, d_i ($1 \leq i \leq N_h$), denotes the length of acoustic link, i , between two adjacent sensor nodes, and
- The parameter, N_h , represents the number of undersea nodes, including the gateway.

In the formalization of the optimization problem, the function $T_{warn}()$ in equation (1) represents the delay difference between the time when the tsunami data reliably arrive at the control station and the time it takes for the tsunami to land ashore. The delay difference must exceed the specified threshold, θ_T , to ensure adequate response to tsunami threats. The function $R_i()$, ($1 \leq i \leq N_h$), in equation (2) represents the reliability of acoustic link i , ($1 \leq i \leq N_h$). The link reliability must exceed the reliability threshold, θ_R , for each link of the infrastructure. Equation (3) represents the constraint on the fiber optic length L , which must exceed a minimum fiber optic length, L_{min} . In practice, this quantity may be a non zero value to comply with local government regulations. A similar reason also applies to the distance between sensor nodes in practice, as expressed in equation (4). It is worth noting that the optimization model does not depend on L_{min} and d_{min} . Therefore, both can be set to a zero value.

The optimization model does not impose any restriction on the distance between adjacent sensor nodes. Therefore, such a distance may be different between any pairs of sensor nodes, depending on the characteristics of the acoustic channel and the environmental ambient noise. The non-uniformity of the distance between adjacent nodes, coupled with the fact that the number of acoustic links, N_h , is an optimization variable, makes the model mathematically intractable.

In the following sections, we derive the objective function of the optimization model. We also express the constraints of the model in terms of the main parameters of the infrastructure and the characteristics of the acoustic channel and undersea environment.

4.1 Infrastructure Cost

The total deployment cost of the proposed infrastructure is the sum of the undersea sensor subnetwork cost, C_S , and the optic fiber segment cost, C_F . In the following, we first derive the cost of undersea sensor subnetwork. We then derive the cost of the optic fiber segment.

4.1.1 Sensor Subnetwork Cost

The cost of the sensor subnetwork can be simply expressed as a linear cost function of a single sensor unit cost. As the number of sensors increases, the infrastructure cost increases linearly. Notice, however, that the subnetwork cost can be generalized to a logarithmic or power-law function to reflect the fact that a “quantity discount” effectively takes place as the number of sensors increases, depending on the nature of application. Generalized cost functions are often used in optimization problems that involve network capacity analysis and provisioning [12].

Let $\rho(r)$ be the cost of a sensor, with rate, r . The cost, C_S , is expressed in Table 1, for different cost functions. The value of α and β , which represent the logarithmic and power-law cost function parameter respectively, vary with the type of the sensor used and are typically characterized by its mean and a standard deviation.

Table 1 Sensor Subnetwork Cost

	Cost, C_s
Linear Cost	$C_s = \rho(r) N_h$
Logarithmic Cost	$C_s = \rho(r) \log(\alpha N_h)$
Power Law Cost	$C_s = \rho(r)(N_h)^\beta$

The cost of a sensor, $\rho(r)$, may vary based on any parameter of the sensor, including capacity and coverage. In this paper, we only consider the capacity as the main contributing factor to the cost. Consequently, $\rho(r)$, can vary in a linear, logarithmic or power law function with rate, r , as illustrated in Table 2. The parameter ϕ_s , represents the unit sensor cost incurred for each unit of rate, expressed in bits per second.

Table 2 Sensor Cost

	Cost, $\rho(r)$
Linear Cost	$\rho(r) = \phi_s \cdot r$
Logarithmic Cost	$\rho(r) = \phi_s \cdot \log(\alpha r)$
Power Law Cost	$\rho(r) = \phi_s \cdot (r)^\beta$

4.1.2 Fiber Optic Cost

The cost of the fiber optic segment, C_F , may vary based on the capacity and length. Consequently, C_F , can be expressed as a linear, logarithmic or power law function of the rate, r , and the length, L . The three cost functions, are illustrated in Table 3.

Table 3 Fiber Optic Cost

	Cost, C_F
Linear Cost	$C_F = \phi_f r L$
Logarithmic Cost	$C_F = \phi_f \log(\alpha r) \cdot \log(\alpha L)$
Power Law Cost	$C_F = \phi_f (r)^\beta \cdot (L)^\beta$

The parameter ϕ_f , represents the cost incurred per unit of transmission rate and unit length, expressed in amount of expenses per bits per second per kilometer.

4.2 Timeliness Constraint θ_T

The timeliness constraint can be derived from the difference between tsunami travel time, $\tau_{tsu}()$, and the delay, $\tau_{Net}()$, it takes a packet originating at the pressure sensor to arrive at the control station. The

tsunami travel time, $\tau_{tsu}()$, depends on the tsunami wave speed, v_{tsu} , and the distance, Δ , from the pressure sensor to the shore. Thus, the timeliness constraint in equation (2) can be re-written as follows:

$$T_{Warn}(L, \mathbf{D}, N_h) = \tau_{tsu}(\Delta, v_{tsu}) - \tau_{net}(L, \mathbf{D}, N_h) \geq \theta_T \quad (5)$$

Tsunami wave speed, v_{tsu} depends on the sea depth at which it travels, which can be approximated by following formula:

$$v_{tsu} = \sqrt{gh} \quad (6)$$

The parameter g , represents the earth gravitational acceleration and h represents the sea depth. The sea depth is directly read from the bathymetry data of the geographical region where the infrastructure is deployed.

However, given the fact that the sea depth varies, the derivation of τ_{tsu} is not straight forward, since the speed varies with depth. To derive τ_{tsu} , the distance Δ is divided into K small segments, Δ_i , where $1 \leq i \leq K$, such that $\Delta = \sum_{i=1}^K \Delta_i$. The depth doesn't change over each small segment, resulting in a constant wave speed v_i . Applying equation (6), this instantaneous speed v_i then can be approximated as follows:

$$v_i = \sqrt{gh^i}$$

Thus, the total tsunami time $\tau_{tsu}()$, over the distance Δ can be approximated as follows:

$$\tau_{tsu}(\Delta, v_{tsu}) \approx \sum_{i=1}^K \frac{\Delta_i}{v_i}$$

The packet network delay, τ_{net} , is the sum of the time spent by the packet at each link. The acoustic link reliability, data length, flow control protocol and acoustic signal propagation time play an important role when computing accurately the link delay. Obviously, the undersea sensor network takes the largest portion of the network latency.

Determining the acoustic signal propagation time accurately is challenging in a changing sea environment. Acoustic waves travel undersea by refraction of the sound. The sound speed is a function of temperature, salinity, depth, and latitude. The propagation time is determined by averaging the arrival times obtained using the Bellhop propagation model.

4.3 Reliability Constraint θ_R

Given a packet of m bits, traveling over a link, i , with bit error rate, BER_i , the probability $R_i(L, d_i)$, that the packet is transmitted successfully to the adjacent sensor node can be expressed as follows:

$$R_i(L, d_i) = (1 - BER_i(L, d_i))^m \geq \theta_R$$

The bit error rate is proportional to the signal quality at receiving node. The signal and sea ambient noise energy dictate the signal quality. More specifically, if $E_b^i()$ represents the acoustic signal energy at the receiving node at link i , and N_0 the equivalent white noise, then the bit error rate can be expressed as:

$$BER_i = F_{pdf} \left(\frac{E_b^i(L, d_i)}{N_0} \right)$$

$F_{pdf}()$ represents a probability distribution function, that, in the case of undersea water, can be reasonably predicted using K-Distribution fading statistics [13].

Computing the energy of the received signal requires determining the transmission loss suffered by the acoustic channel. There are two types of loss to be considered, namely spread and absorption loss. A total transmission loss, A , of an acoustic signal traveling over a distance, d , with frequency, f , can be expressed as follows:

$$A = d^k a(f)^d \quad (7)$$

The term d^k accounts for spread loss, where k is the spreading factor and d denote the distance between transmitting node and receiving node. The term $a(f)^d$ accounts for the absorption loss. The spread loss occurs due to the geometric spreading of acoustic wave outward from the source [14]. There are two common assumptions for geometrical spreading. They are spherical ($k = 2$) and cylindrical spread ($k = 1$), depending on the characteristics of the medium and location of the source node or transmitter. Acoustic absorption loss is the loss due to absorption by material of the medium and acoustic energy transformation (i.e. heat). In this paper, we utilize the empiric formula defined by Thorp [14][15] to describe the absorption loss.

However, equation (7) does not give the detail of how acoustic signals suffer loss due to the geometry of their path trajectory and their interaction with the sea environment, depending on whether they are refracted by sea water, or reflected by sea surface and sea floor. Hence, the use of equation (7) for higher accuracy may lead to an incorrect result. To obtain correct values of transmission loss, with high accuracy, the Bellhop acoustic propagation model is used.

Bellhop is a finite element model based on Ray Tracing theory for acoustic waves. Although it has coarser accuracy compared to other models such as Normal Mode or Parabolic Equation, a Ray Tracing Theory tends to improve in high frequency, especially above 1 KHz. Further, a Ray Tracing model can be used to capture the acoustic propagation characteristics and serve as the baseline to interpret the results of other acoustic propagation models. The Bellhop model was developed by [9]. An applications suite is written to run Bellhop acoustic propagation model. [16] provides the guide on how to use this applications suite. This application suite provides quantities needed in the optimization model, such as acoustic transmission loss and acoustic propagation time.

The use of the Bellhop suite requires a number of environment data to be supplied. Only the most relevant parameters to the optimization model will be discussed. The first type of sea environment data is

the undersea sound speed. Undersea sound speed is governed by three parameters, namely water temperature, depth, and salinity. Many empirical formulas have been derived to calculate undersea sound speed. Various empirical formulas to calculate undersea sound speed, based on these three parameters, are described in [17]. Different sound speeds across the sea water depth layers impact the trajectory of acoustic waves propagation due to refraction. The Bellhop model captures this phenomenon and allows an accurate computation of the acoustic wave transmission loss. The second parameter represents the sea depth profile between the transmitter and receiver. The profile data are required to determine how the acoustic waves are reflected as they reach the sea floor. We use the bathymetry file to obtain sea floor profile. Figure 3 illustrates how an acoustic signal propagates in a dynamic sea environment.

Figure 3 : Transmission of an acoustic signal from a 600-meter depth source to the coast line

In addition to transmission loss, the ambient noise, also referred to as background noise, interferes with the acoustic signal. If the noise is strong enough, the original signal may no longer be recognizable, causing the receiver to discard it. There are several main contributors of sea ambient noise. They include water motion due to the effect of rain, surf, hail and tides. Man made noise sources, such as ship activity, and marine life also contribute to the sea ambient noise. The impact of each source depends on the acoustic frequency used. Generally, the ambient noise increases in the shallower sea depth [18]. Numerous sea ambient noise measurements and studies were conducted. Some efforts, such as the work in [10], summarize the sea ambient noise. The summary is captured in a group of curves, referred to as the Wenz curve, depicted in Figure 4.

Figure 4: Wenz curve, adopted from [10] and [14]

The Wenz curve is used in this study to obtain an approximation for the undersea ambient noise. The derived approximation of the ambient noise spectrum is represented by the thick dashed line in Figure 4. This line is derived so that the ambient noise is equivalent to that observed by the sea state scale between 3 to 4. Within this scale range, it can be inferred, based on Table 1.6 in [14], that the average height of sea waves can be estimated to range between 3 and 4 meters.

5 Application of the Model

The optimization problem is NP-hard [20]. Consequently, the derivation of the optimal solution is computational expensive. A heuristic approach is used to derive an approximate solution.

5.1 Heuristic Approach

The proposed heuristic is based on the following observation: The least-cost infrastructure can be obtained by an all-sensor network. Such a network configuration, however, may not meet the reliability and timeliness constraints. An all-fiber optic network, on the other hand, can be designed to meet these constraints, but at the highest cost. The heuristic approach attempts to achieve a tradeoff between the reliability and low delay of the fiber and the low cost of the sensor nodes.

Assuming a fiber optic data rate, r , and using equation (5), the exact length of the optic fiber, $L = \Delta_{min}$, to meet the time constraint, θ_T , in an “all fiber” configuration, can be derived. This is achieved by determining the furthest location of the pressure sensor that guarantees that if a tsunami is detected at this location, then the transmitted optical signal will reach ashore no later than θ_T units of time after detection. Δ_{min} drives the initial step of our heuristic approach. Starting with Δ_{min} , the heuristic gradually reduces the length of the fiber and augments the network topology with an acoustic link. The reliability and timeliness constraints are then checked. If no violation of these constraints is observed, we further reduce the fiber length and interject a new sensor. This iterative step is referred to as the “inbound link replacement”, as it progresses toward the coast. We then calculate the total deployment cost, which is compared with the cost of the previous configuration. The iterative process terminates whenever the cost of the previous configuration is cheaper than the cost of the current one.

However, if the timeliness constraint is violated, two methods are used to overcome this violation. In the first method a simple binary search is applied to find the length of the extension needed to meet the timeliness requirements. At each step, the length of the acoustic inbound link is reduced, while the length of the fiber optic is increased. The second method moves the pressure sensor location further away from the shore to detect the near-field tsunami earlier. The method that leads to the cheaper solution is used and the resulting configuration is selected. Note that the second method will not be feasible if the acoustic signal propagation speed is slower than the tsunami propagation speed. Since the detection of a near-field tsunami assumes that the pressure sensor node cannot be located at distance, Δ_{max} , that exceeds the epicenter, the heuristic will always produce a network configuration with near-optimum cost, if one exists. However, if an all-optic fiber network of length, Δ_{max} , that extends from the control station to the epicenter cannot satisfy the timeliness requirements, no feasible solution is possible. Figure 5 describes the basic steps of the proposed heuristic.

5.2 Tools

We developed a Matlab program to implement and evaluate the proposed heuristic for the optimization model. We utilize Matlab’s optimization tool to determine the maximum length of the acoustic link that meets the reliability constraint. This is achieved by first invoking the relevant program in the Bellhop suite, with the underwater sound speed and the sea floor profiles as parameters. The Bellhop program calculates and returns the values of the transmission loss and propagation time. In addition to these two environment factors, the Matlab program determines the ambient noise using the pre-defined ambient noise function depicted in Figure 4. These values are then entered into the Matlab program to compute the link reliability. This value is used by Matlab’s optimization tool to determine the maximum length of the acoustic link that meets this reliability constraint. Figure 6 illustrates how different tools are integrated to produce the final solution of the optimization model.

Figure 5 : Heuristic approach flowchart

Figure 6 : Diagram block of the integration of the tool

6 Case Study

To explore the feasibility of the proposed heuristic approach, a case study is conducted. Since the cost functions play important role on the optimization model, the analysis is aimed to seek the feasibility of the proposed approach when different application requirements and cost scenarios are applied.

However, this case study analysis is not intended to validate the correct cost function. A further research and study should be made to determine the most appropriate cost function for each network components.

6.1 Model Parameters

The case study is focused on Padang City. A set of constants and parameters, along with the constraint thresholds, are specified. Their values are shown in Table 4.

Table 4 : Assumptions and Parameters

Constants and Parameters	Value	Remarks
Tx Power	40 Watt	
Modulation	Binary Frequency Shift Keying (BPSK)	
Data Link Protocol	Stop and Wait	
Data size (m)	120 bits	
Bit Error Probability Distribution Function	K-Distribution Function	See work in [13] for BPSK modulation.
Acoustic Frequency f	6 KHz	
Ambient Noise Approximation	$125 - 20\log_{10}(f)$	Equation for ambient noise spectrum approximation in Figure 3. Frequency f is in Hz
L_{min}	10 Km	
Δ_{max}	90 Km	
Optic fiber transmission rate	500 Mbps	
θ_T	{12,13,...,22,23,24}	In minutes
θ_R	{0.7, 0.725,...,0.99,0.995,0.999}	Can be expressed in percent (i.e.. 0.7=70%)
Sensor transmit rate	{60, 80,...,260, 280, 300}	In bit per second
γ	{0.05, 0.1,0.3, 0.5,...,1.9, 2.1, 2.3}	Unit cost ratio
α	1.4	Logarithmic cost parameter
β	1.4	Power-law cost parameter

The heuristic of the optimization model is applied with the different design parameters. For each case, the results are analyzed and discussed for three different cost scenarios: linear, power-law, and logarithmic. In the cost analysis, the undersea sensor unit cost, ϕ_s , is expressed in relation to the unit cost of optic fiber, ϕ_f , as $\phi_s = \gamma \phi_f$, where γ is a constant. Furthermore, the cost of the most expensive all-optic fiber solution is used as the baseline cost, when comparing the cost of the different network configurations, obtained using the design parameter values described in Table 4. We also assume that the initial cost, C_0 , for both fiber optic and undersea sensor node network to be the same. Finally, the detection time is assumed to be negligibly small.

6.2 Underwater Sound Speed Profile and Sea Bottom Profile

Figure 7 and Figure 8 show the undersea sound speed and sea floor profiles of the Padang City area [19]. Figure 7 shows that the sound speed drops rapidly at depths around 100 to 200 meters. It continues to drop at deeper depths, but at a lower rate. The trend is reversed and the sound speed increases at a depth of about 800 meters. The sea floor profile, depicted in Figure 8, shows that the terrain exhibits a relatively steep slope between 20 km and 70 km off shore.

Figure 7 : Undersea sound speed profile for the case study area

Figure 8 : Sea bottom profile at case study area

6.3 Minimum Detection Distance Δ_{min}

Equation 5 is used to determine the value of Δ_{min} (or equivalently L_{max}), required for the initial step of the proposed heuristic. The resulting values of Δ_{min} , correspond to the different values of θ_T listed in Table 4 are shown in in Table 5.

Table 5: The list of minimum detection distance for designated time constraints.

θ_T (Minutes)	12	13	14	15	16	17	18	19	20	21	22	23	24
Δ_{min} (Km)	18.8	20.4	22.0	23.6	25.2	27.1	29.2	31.9	35.5	39.7	44.4	49.5	55.0

6.4 Results and Discussion

There are three different cases of design parameters set to analyze under three cost scenarios. In the first case, the paper discusses the impact to the total cost and the network configuration when the undersea sensor transmission rate and reliability constraint are varied. The discussion continues to the results impacted by the changes of cost ratio, γ , and reliability constraint, θ_R . In the last case, the paper focuses on the optimal results as the timeliness θ_T and reliability θ_R are varied.

6.4.1 Optimal Results under Different Sensor Transmission Rates and Reliability Constraints

Figure 9 demonstrates the total deployment cost C_{Tot} computed with both undersea sensor and fiber optics parameters, in linear, power-law, and logarithmic format. For this case study, we set $\gamma = 0.2$ and $\theta_T = 15$ minutes.

Figure 9 : Total cost C_{Tot} at cost function (a) linear (b) Power-law (c) Logarithmic

As we can observe in Fig. 9(a) and 9(b), the models exhibit similar pattern of results, where the cost increases significantly at a reliability higher than 95%. The significant increase is seen at the higher transmission rate. At reliability of 95% or less, we may deduce that the total cost plane is relatively proportional to the node's transmission rate. However, the total cost returned by our heuristic approach at

very high reliability (larger than 95%) may give misleading results in the logarithmic cost function. In Figure 9(c), the total cost doesn't seem to change gradually when very high reliability is applied.

To have this finding, we observe the total cost computation and attempt to identify whether a local maximum may exist, when our heuristic approach runs. To explore this possibility, we select a sensor's transmission rate of 100 bps, with reliability of 99.9%, and then analyze the results under three different cost scenarios. We observe the total cost C_{Tot} computation through out the heuristic steps. To do this, we record all the computed costs and keep performing the steps, even if the cost in the previous iteration is cheaper than the subsequent one.

In this combination, in the logarithmic cost function, a local maximum exists when the number of sensors equals to 2 (inbound and outbound are added simultaneously), as shown in Figure 10(c). Then the cost starts to decrease as the number of sensors increases and stops when the minimum fiber optic length is encountered. This finding, however, confirms the incorrect results demonstrated in Figure 9(c), where the optimal solution is all-fiber optic deployment.

However, this implication does not appear either in the linear and power-law cost function at the same parameter combination. Both cost functions return a monotonic decrease of total cost when the number of nodes is increased, as illustrated in Figure 10(a) and 10(b). Thus, this result gives an example that the algorithm may fail in this particular case.

Figure 10 :The dynamic change in total cost in a heuristic approach.(a) Linear (b) Power-law (c) Logarithmic

Nevertheless, Table 6 lists several optimal configurations of the proposed infrastructure in two different values of reliability constraints and the linear cost function. We select 95% and 99.9% for the reliability constraints with sensor transmission rate of 100 bps. At the reliability of 95%, our model returns three undersea sensors to deploy. If the infrastructure is required to operate with reliability of up to 99.9%, then our optimization model returns seven sensors to deploy for the optimal result. Note that both reliability constraints maintain the fiber optic at its minimum length L_{min} .

Table 6 : The underwater acoustic links for designated reliability constraint with $\theta_T=15$ minutes

θ_R	Acoustic Link Length (Km)							L (Km)
	d_1	d_2	d_3	d_4	d_5	d_6	d_7	
0.95	5.60	9.82	3.78	-	-	-	-	10.0
0.999	0.75	2.54	2.28	2.41	2.36	2.10	1.88	10.0

As we can observe from Table 6, to set infrastructure reliability to 99.9% requires the number of sensors as twice as the one at 95% reliability. If two undersea sensor networks with 95% reliability are placed in parallel, while retaining single fiber optic link, then a 99.8% reliability will be achieved, assuming that one of them is assigned as the redundant or backup network. Although it offers 0.1% less than our defined highest reliability, this result benefits one less undersea sensor. Furthermore, a 0.1% reliability difference will not have significant impact in practice.

6.4.2 Optimal Results under Different Unit Cost Ratio γ and Reliability Constraint

In the second case, we focus the discussion on how the optimal results will be affected by variation in unit cost ratio γ and reliability constraint. To conduct the analysis, the same timeliness constraint and sensor transmission rate are set (15 minutes and 100 bps respectively). Figure 11(a), 11(b), and 11(c) show the results when the cost functions are in linear, power-law and logarithmic formats for both the fiber optic cable and undersea sensor network.

Figure 11 : Total cost C_{Tot} at cost function (a) linear (b) Power-law (c) Logarithmic

According to the cost functions formulation for all three types, the unit cost ratio only affects the outcome in linear relation. Given the current assumptions, at the same reliability value, the cost increases linearly for all cost scenarios. In the linear scenario, since all factors are linear, the most likely solution is all fiber optic deployment, especially when the reliability constraint is larger than 0.975 (indicated by flat surface on the top). In the power-law cost function, the all fiber optic solution is achieved at much higher cost ratio γ . This is because the unit cost ratio is the only linear factor in the power-raised cost function, whereas the rest is raised by the power coefficient α .

Again, an interesting finding is depicted by logarithmic cost function in Figure 11(c). At this point, all-fiber optic deployment is the optimal solution for the most of the design parameters, even when the sensor unit cost is cheaper than fiber optic unit cost. To confirm this finding, we conducted a similar observation as the one made in the first case.

Our further analysis shows that our heuristic approach does not always return incorrect results. For example, we select $\gamma = 0.3$ and $\theta_R = 99.5\%$ as the test case. The dynamic of implementation costs is shown in Figure 12(a). At this point, it indeed exhibits a local maximum and eventually the heuristic algorithm returns an incorrect result. However, a different outcome is found for $\gamma = 0.7$ at the same reliability constraint. Although it demonstrates a local maximum shown by Figure 12(b), the total cost C_{tot} incurred by 4 sensors and a minimum length of fiber optic cable is still higher than the one incurred by all-fiber optic deployment. In this case, our approach returned correct solution (hence, an all fiber optic deployment is the optimal result).

To see another different outcome, we keep the cost ratio γ at 0.7, but setting a lower reliability constraint at 90% for the test case. Figure 12(c) demonstrates a monotonic increasing pattern. In this case, our heuristic approach returned the correct result again, where all optic fiber deployment is the optimal solution.

Figure 12 : The dynamic of total cost with (a) $\gamma = 0.3, \theta_R = 0.995$ (b) $\gamma = 0.7, \theta_R = 0.995$ and (c) $\gamma = 0.7, \theta_R = 0.9$. The x axis denotes the number of sensors and y axis denotes the cost.

6.4.3 Optimal Results under Different Timeliness and Reliability Constraints

This section provides the discussion on how the network configuration and its deployment cost will be affected by the change of timeliness constraint θ_T and reliability constraint θ_R . The following results and discussion are appealing for those who are involved in developing tsunami hazard mitigation efforts. In this case analysis, the cost ratio γ is set equal to 0.2, while the node's transmission rate remains at 100 bps. In contrast with the previous cost analysis, the results express the deployment costs C_{tot} as their ratio to the minimum deployment cost. Obviously, it is obtained at the lowest reliability θ_R and the shortest timeliness constraint θ_T in our design parameters set. Thus, the total deployment cost C_{tot} will be

normalized to the one achieved with θ_R equals to 70% and θ_T equals to 12 minutes. Figure 13 shows the results for linear, power-law, and logarithmic cost function.

Figure 13 : Total cost C_{Tot} at cost function (a) linear (b) Power-law (c) Logarithmic

Our optimization model demonstrates similar behavior of the total cost for both linear and power-law cost function. A reliability constraint lower than 95% exhibits insignificant increase on the total cost with the increase of timeliness constraint. For example, in linear cost function, it only costs about 15 percent more to implement 24 minutes time constraint with the reliability of 95%, in comparison to those with 12 minutes time constraint and the same reliability constraint. These results might be appealing in tsunami hazard mitigation because it is preferable to have more time to evacuate without incurring significant increase in the deployment cost.

However, the results given by the logarithmic cost function scenario are noteworthy. The smooth top surface indicates that the optimal solutions are all-fiber deployment. The transition from lower surface to the top seems to occur abruptly. This result is intriguing. At least, we already observed that it returned incorrect result for $\theta_T=15$ minutes and $\theta_R=99.9\%$, as discussed in the previous section. We may check the dynamic of total cost for a lower reliability constraint, such as $\theta_R=95\%$ at the same time constraint. Figure 14 demonstrates a monotonic decrease when the number of nodes increases. Hence, in this sample point, the heuristic approach returns correct result.

Figure 14 : The dynamic of the cost for logarithmic cost function with $\theta_T = 15$ min and $\theta_R=0.95$

In spite of these pitfalls in logarithmic cost function, we show examples of optimal configurations in Table 7 when different time constraints are assigned. Table 7 summarizes the optimal results for the proposed infrastructure, given $\theta_T = \{15, 18, 20, 24\}$ minutes with reliability constraint $\theta_R = 0.95$. These configurations are obtained using linear cost function.

Table 7 : The configuration of proposed infrastructure at $\theta_T = \{15, 18, 20, 24\}$ and $\theta_R = 0.95$

θ_T (Minutes)	Acoustic Link Length (Km)						L (Km)
	d_1	d_2	d_3	d_4	d_5	d_6	
15	5.60	9.82	3.78				10
18	8.27	8.73	8.84	1.63			10
20	8.50	8.18	8.10	8.13	1.08		10
24	8.80	10.27	9.92	8.59	8.06	8.16	10

7 Conclusion

We proposed a cost-effective infrastructure for near-field tsunami detection that combines optical fiber infrastructure and undersea sensor network. We formulated a cost optimization model for corresponding infrastructure. We incorporate environmental factors and Bellhop acoustic propagation into our optimization model and provide a heuristic approach to solve the problem. This approach returns more effective results, if no local maximum exists in the total cost of infrastructure. In our case study, further assessment should be made on the logarithmic cost function scenario, especially with a very high reliability constraint.

However, these results are obtained using stated underlying assumptions and several empirical models. Using real data from measurement would improve the result significantly. Also, incorporating network maintenance cost into our cost model would be indeed giving more accurate result.

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Nomenclature

Following table summarizes the symbols and notations that are used in this paper.

Symbols	Remarks
τ_{tsu}	The tsunami travel time
Δ	The distance between the pressure sensor node and the location of the control station
Δ_{max}	The maximum Δ
Δ_{min}	The minimum Δ that satisfy the timeliness constraint
L	The optic fiber length, in km
L_{min}	The minimum length of optical cable from the shore imposed by regulation, if applicable.
L_{max}	L of the most expensive feasible solution
d_i	Distance between adjacent undersea sensor at link i
N_h	The total number of unit of underwater sensors
T_L	Propagation time in optic fiber
$T_{Warn}()$	Warning time constraint function
h	The sea depth
C_{Tot}	Total deployment cost
C_F	The cost to implement optic fiber link of the proposed infrastructure
C_S	The cost of undersea sensor subnetwork of the proposed infrastructure
θ_T	The timeliness constraint imposed by regulation
θ_R	The reliability constraint
v_{tsu}	The tsunami propagation speed
r	Transmission rate, in bit per second
ϕ_s	Undersea sensor unit cost per unit transmission rate
ϕ_f	Optic fiber unit length cost per unit transmission rate
α	Parameter for logarithmic cost function
β	Parameter for power-law cost function
γ	Ratio of sensor unit cost and optic fiber unit cost
f	Acoustic wave frequency, in Hz

k	Spreading factor, where $1 \leq k \leq 2$
g	The acceleration of earth gravitation
$\alpha()$	The absorption loss factor function
A	The total acoustic channel loss
$R_i()$	Reliability constraint function at link i
N_0	The equivalent white noise
$E_b^i()$	Energy per bit at link i
m	Packet length, in bit

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