A Decision Theoretic Framework for Selecting Source Location Privacy Aware Routing Protocols in Wireless Sensor Networks

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Abstract

Source location privacy (SLP) is becoming an important property for a large class of security-critical wireless sensor network applications such as monitoring and tracking. Many routing protocols have been proposed that provide SLP, all of which provide a trade-off between SLP and energy. Experiments have been conducted to gauge the performance of the proposed protocols under different network parameters such as noise levels. As that there exists a plethora of protocols which contain a set of possibly conflicting performance attributes, it is difficult to select the SLP protocol that will provide the best trade-offs across them for a given application with specific requirements. In this paper, we propose a methodology where SLP protocols are first profiled to capture their performance under various protocol configurations. Then, we present a novel decision theoretic procedure for selecting the most appropriate SLP routing algorithm for the application and network under investigation. We show the viability of our approach through different case studies.

Keywords: Source Location Privacy, Wireless Sensor Networks, Decision Theory, Technique Comparison

1. Introduction

A wireless sensor network (WSN) consists of a number of tiny devices, known as sensor nodes or motes, that can sense different attributes of the environment and use radio signals to communicate among themselves. WSNs have enabled the development of many novel applications, including asset monitoring, target tracking and environment control [1] among others, with low levels of intrusiveness. They are also expected to be deployed in safety and security-critical systems, including

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DOI: https://doi.org/10.1016/j.future.2018.01.046

military [2] and medical services. The communication protocols used in the WSNs must therefore meet a set of stringent security and privacy requirements dependent on the application.

Threats to privacy in monitoring applications can be considered along two dimensions: (i) content-based threats and (ii) context-based threats [3]. Content-based privacy threats relate to use of the content of the messages broadcast by sensor nodes, such as gaining the ability to read an eavesdropped encrypted message. There has been much research addressing the issue of providing content privacy, e.g., SPINS [4], with most efforts in this area focusing on the use of cryptographic techniques. On the other hand, context-based privacy threats focus on the context in which messages are broadcast and how information can be observed or inferred by attackers. Context is a multi-attribute concept that encompasses situational aspects of broadcast messages, including environmental and temporal information.

It is often desirable for the source of sensed information to be kept private in a WSN. For example, in a military application, a soldier transmitting messages can unintentionally disclose their location, even when encryption is used. Another example is during the monitoring of endangered species where poachers may be tempted to infer the location of the animal to capture it. Real world examples include monitoring badgers [5] and the WWF's Wildlife Crime Technology Report [6], both of which would likely benefit from a context-based security measure. In this paper, the context we focus on protecting is the *source location*.

Techniques that protect this source location are said to provide source location privacy (SLP). SLP is important in many application domains, though it is of utmost concern in security-critical situations. In each of these scenarios, it is important to ensure that an attacker cannot find or deduce the location of the asset being monitored, whether it is a soldier or an endangered animal. A WSN designed to forward the information collected about an asset would typically consist of the following: a dedicated node for data collection called a *sink node*, the node(s) involved in sending information about these assets called *source nodes*, and many other nodes in the network used to route/relay messages over multiple hops from the sources to the sink. It has been shown that even a weak attacker such as a distributed eavesdropping attacker can backtrack along message paths through the network to find the source node and capture the asset [7]. Thus, there is a need to develop SLP-aware algorithms.

A number of techniques have been proposed to provide SLP, such as phantom routing using random walks [7], delays [8], dummy data sources [9, 10] and many others [11]. In general, the objective can be informally stated as the provision of a high level of source location privacy while spending as little energy as possible. Thus, the various techniques basically navigate this trade-off solution space. However, when several conflicting objectives are involved, navigating this space becomes more challenging. Thus, in this paper, we propose a methodology where routing protocols are first profiled to capture their performance according to the desired set of metrics. Then, we use a decision theoretic procedure for selecting the most appropriate SLP routing algorithm for the type of network and application under study. We show the viability of our approach through various case studies and show how the suitability of different SLP protocols vary according to the application under study.

Thus, the main contributions of this paper are:

- We propose a 2-step methodology for SLP-aware protocol selection: (i) profiling of protocols and (ii) selection of a protocol.
- The protocol selection step is based on a decision theoretic procedure that first removes dominated protocols and then formalizes the notion of relevance using suitable utility functions.
- We show, through the use of various case studies, the impact that the application has on the suitability of the SLP protocols.

The remainder of this paper is organised as follows: Section 2 surveys related work in SLP and Section 3 presents the models assumed. We present the relevant routing protocols we consider in this paper in Section 4. In Section 5, we present the decision theoretic procedure for selecting the most appropriate SLP-aware routing algorithm. The adopted system and simulation approach are outlined in Section 6. In Section 7 we present an example of the execution of the decision theoretic procedure. Section 8 presents three case studies to showcase the viability of the approach. Section 9 concludes this paper with a summary of contributions.

2. Related Work

2.1. Overview

The concept of the SLP problem was first posed around 2004 in [12] which proposed the panda-hunter game where the poachers only used network traffic flow to track the panda. Kamat formalised the SLP issue based on the panda-hunter game [7]. Since then, several techniques have been proposed to address SLP. The solution spectrum spans from simple solutions such as simple random walk [12] to more sophisticated techniques such as fake sources and diversionary routing in [10, 13, 14, 15].

2.2. Phantom Walk Technique

In the seminal work [12], the authors proposed a solution called *phantom routing*, where messages were sent on a directed random walk where the message was either sent towards or away from a certain node in the network, followed by using the flooding routing protocol. A similar approach to phantom routing was used in [7]. Instead of using flooding, they used single path routing protocols, such as shortest path routing. The combination of the random walk together with such single path routing is often referred to as the phantom single-path routing scheme (PSRS). Phantom routing and PSRS has received a lot of attention in literature. On the other hand, this class of solution is known to have weaknesses as demonstrated by [16, 17, 18], ascribing poor SLP performance to the directed random walk reusing the routing path and exposure of direction information.

For other random walk algorithms, an improvement of the directed random walk was introduced in [19], with the introduction of the self-adjusting directed random walk (SADRW). The neighbours were divided into four different sets, and nodes randomly pick a neighbour out of one of the four directional sets and send the messages to it. A new algorithm using location angles was proposed to construct the random walk based on the inclination angle between a node and its neighbour towards the sink [20]. The author Xi introduced the greedy random walk (GROW) [21]. In GROW, one random walk starts from the sink and goes to a randomly chosen receptor-node. The other random walk starts from the source and meets the first random walk at the receptor-node. Then, the receptor-node uses the path established by the random walk from the sink to the receptor-node to route the packet from the source to the sink. Besides, the authors used a different approach, by recording neighbours in a bloom filter which informed the choice of the next node to be used in the random walk [21]. However, there is still scope to improve the nodes that are allocated to take part in the directed random walk. Other algorithms use the random walk technique to address the SLP issue such as randomly selected intermediary node (RRIN) [22], random routing scheme (RRS) [23] and phantom walkabouts [24].

2.3. Fake Source Technique

Algorithms utilise dummy messages sent by a *fake source* to provide SLP. Some nodes are chosen as fake sources and periodically send dummy messages to obfuscate the real traffic. In the early stages, the author Ozturk introduced a concept of fake sources and propose a theoretical algorithm called short-lived fake source routing (SLFSR) [12]. Later on, many algorithms have been proposed with state-of-the-art fake message techniques [10, 25, 26, 27, 28]. These algorithms based on the fake source mentioned so far can only provide SLP against the local attacker.

For the scope of the global attacker, a global protection scheme called Periodic was developed in which every node sends a message after a fixed period [29]. This provided perfect protection against an attacker with a global view of the network. The authors created a model involving traces of source detection, which was used to measure the privacy of those traces as well as the energy cost of providing SLP. In addition, a different approach where statistical techniques were used to show that their global protection scheme provided high levels of SLP [14]. This approach did not provide perfect global SLP as [29] did, but instead provided statistically strong SLP. Their model and solution aimed to make the distribution of message broadcasts from nodes indistinguishable from a certain statistical distribution.

Other techniques consist of a hybrid between generating fake messages and having messages modify their routing path. Tree-based diversionary routing [15] which imposes a tree structure on the network and then routes fake messages through the tree. Similarly, fog or cloud techniques [30, 31] have been proposed to provide SLP where a normal message is routed through a group of nodes called a fog and then onwards to other fogs.

Perhaps the most significant disadvantage of the described fake source techniques is the volume of messages broadcast to provide SLP. This leads to increased energy consumption and an increased number of collisions, both of which result in a decreased packet delivery ratio. This means that a tradeoff between energy expenditure and privacy must be made [26], making dummy message schemes challenging for many large-scale networks.

2.4. Other Techniques

Apart from techniques described above, an algorithm was proposed where nodes changed the chronological order of received messages and sent messages which also change the traffic pattern, making it hard for a local adversary to track the traffic to the source node [8]. Wang used separate path routing to transmit messages, leading to less packets per path, making it harder for the adversary to track messages back to the real source [16]. Mules-saving-source protocol (MussP) use α-angle anonymity to provide SLP by adopting data mules which collect the packets from sources and drop them elsewhere [32]. Others include using geographic routing [17] and network coding [33, 34] to address the SLP issue.

3. Models

In this section, we present the various models that underpin this work.

3.1. Network Model

We assume a wireless sensor network to contain a set of resource-constrained nodes that communicate among themselves using radio. When a node senses the environment, it generates a message and sends the message towards a dedicated node called the sink. There are several potential routing algorithms for WSNs. We assume all the nodes to be static, i.e., the topology of the network remains constant as well as the neighbourhoods of all the nodes over the lifetime of the network. We do not assume that links are bidirectional, i.e., links may disappear intermittently.

3.2. Attacker Model

We assume a patient adversary model, known as a *distributed eavesdropper*, introduced in [7]. The attacker initially starts at the sink and we assume the attacker is equipped with the necessary devices to determine the direction a message originated (such as directional antennas). When the attacker overhears a new message, they will move to the location of the immediate sender, i.e., the neighbour that last forwarded the message. This is commensurate with the attacker model used in [10, 26, 27, 35, 36].

4. Routing Protocols Review

In this section, we will review the SLP-aware routing protocols that will be analysed in this paper. However, the framework we propose can be extended to handle any other SLP-aware routing protocol.

4.1. Protectionless Flooding and Protectionless CTP

Two routing algorithms that provide *no* SLP will be evaluated in this work to compare against the SLP techniques. The first is flooding in which a source floods a message through the network, by having each node that receives it forwarding it. Flooding is included as it was shown by the seminal work to provide no SLP [7]. The second is CTP [37] (the Collection Tree Protocol) which uses the expected number of transmissions to gauge the reliability of a link to form a routing tree from every node in the network to the sink. CTP is included as it is the state-of-the-art reliable routing protocol for WSNs. No work thus far has analysed its ability to provide SLP.

4.2. Phantom Walkabouts

Phantom walkabouts is an algorithm using a random walk technique to provide SLP [24]. The new technique, which uses a mix of short and long random walks, achieves a higher level of SLP than phantom routing with a bounded message overhead. Authors denote a phantom walkabouts parameterisation by $PW(m_s, m_l)$, where m_s and m_l denote the number of short and long random walks respectively to be performed in a cycle. When a source node routes a message M using phantom walkabouts, a decision is needed regarding whether M goes on a short or long random route. The sequencing of messages is as follows:

$$\underbrace{M_s, \cdots, M_s,}_{m_s}\underbrace{M_l, \cdots, M_l,}_{m_l}\underbrace{M_s, \cdots, M_s,}_{m_s}\underbrace{M_l, \cdots, M_l,}_{m_l}\cdots$$

For instance, $PW(1, 1)$ denotes a repeating sequence of 1 short random walk followed by 1 long random walk. Therefore, we observe that phantom walkabouts consists of m_s messages on short random walk M_s and m_l messages on long random walk M_l, before the cycle is repeated.

4.3. DynamicSPR

DynamicSPR is an extended version of the Dynamic fake source technique [27]. In Dynamic, fake sources are allocated away from the real source and sink in order to provide a *pull* in that direction. The technique dynamically determines parameters online to be able to adjust to a changing network environment. DynamicSPR [38] optimises the way fake sources are allocated, such that the fake sources perform a directed random walk away from the sink. This reduces the number of fake sources present in the network and also the number of messages the technique sent (thus reducing the energy usage).

4.4. ILP Routing

In ILP Routing [39], the problem of SLP-aware routing of messages from a source to a sink was modelled as an Integer Linear Programming (ILP) optimisation problem. Using an ILP solver an optimal solution was obtained when trying to maximise the attacker's distance from the source. As the optimal solution required global knowledge, the authors implemented a distributed version that had a message take a directed walk around the sink to approach it from a direction other than the one the source was in. Messages were delayed by different amounts such that they reached a similar point at a certain distance. By doing this the attacker makes less progress, due to messages being grouped at a similar location and also because messages would be missed that take a different path.

5. Decision Theoretic Procedure for Selecting Routing Algorithm

Given the number of SLP-aware routing protocols, each one optimizing one or more attributes, it becomes challenging to select a protocol for a given application. For example, if an application requires a high level of privacy and is supposed to run for a short time, selecting a protocol that trades-off privacy for lower energy consumption will not be suitable. Thus, there is a need to develop a framework that can guide a network or application designer in selecting the appropriate SLP-aware routing protocol.

In this section, we are thus concerned about structuring the preferences to simplify the trade-off analysis. As we are concerned about multi-attribute optimization, we provide a brief overview of the theory underpinning generation of multi-attribute utility functions. Table 1 summarises the most commonly used symbols in the paper.

5.1. Brief Introduction to Decision Theory (DT)

We refer the readers to [40, 41] for details about multi-objective optimization. Very often, real-world cases deal with more than three attributes. We assume that we have n evaluators, $E_1, E_2, \dots E_n$, evaluating attributes $a_1, a_2, \dots a_n$ respectively, such that $(E_1(a_1), E_2(a_2), \dots E_n(a_n)) = (q_1, q_2, \dots, q_n)$, where each q_i captures the "performance" of the protocol for a particular attribute and the vector $(q_1, q_2, \dots, q_n)$ is the "performance" vector of a protocol. An overall relevance function, G, may be expressed in additive form

$$G(q_1, q_2, \dots, q_n) = \sum_{i=1}^{n} (\lambda_i * G_i(q_i)) \tag{1}$$

where G_i's are single-attribute or individual relevance functions [40, 41], and $\sum_{i=1}^{n} \lambda_i = 1$ iff the attributes are *mutually preferentially independent*, i.e., trade-off between pairs of attributes is independent of the values of other attributes. Such a property is important to keep the selection "local", i.e., the trade-offs between a pair of attributes need not consider the values of *all* other attributes.

Table 1: Commonly used symbols

Symbol	**Description**
c	Network configuration
$\mathcal{P}$	Name of a given protocol
$r_{\omega}^{c,\mathcal{P}}$	Result of a attribute under c and $\mathcal{P}$
$R_{\omega}^{c,\mathcal{P}}$	Normalised Result of a attribute under c and $\mathcal{P}$
$r^{c,\mathcal{P}}$	Result vector of all attributes under c and $\mathcal{P}$
$R^{c,\mathcal{P}}$	Performance vector of all attributes under c and $\mathcal{P}$
$U_{\omega}^{c,\mathcal{P}}$	Utility of a single attribute under c and $\mathcal{P}$
$U^{c,\mathcal{P}}$	Utility of performance vector under c and $\mathcal{P}$
u_a	Aspiration vector
λ_{ω}	The weight of a single attribute
Δ_{ss}	Distance between sink node and source node
tt	Flooding time taken
sp	Safety period

A higher value of λ_i is indicative of a higher importance of the corresponding attribute. Thus, to generate the overall relevance function, each λ_i needs to be determined, subject to the constraint $\sum_{i=1}^{n} \lambda_i = 1$. Also, each individual relevance function G_i needs to be generated by the system administrator or application developer. Determining an accurate G_i is a challenging process. We direct the interested reader to [40, 41] for more information about generating such functions, which is however beyond the objective of the paper. We will use *arbitrary* functions to showcase the decision theoretic methodology we propose in the paper.

5.2. Decision Theory-Based Heuristic

In this section, we present a novel two-step decision procedure (or heuristic) that helps choose the most suitable SLP-aware routing algorithm from a set of contenders for a given application:
Step 1 - Profiling and Filtering

1. For various network configurations (size, safety factor, noise models etc), run all the protocols to obtain their respective performance profiles, i.e., generate their performance vectors. This step can be done once and the profiles stored in a database or library.
2. Determine all decision attributes for the application, e.g., latency, delivery ratio or capture ratio. If the attributes are not mutually preferentially independent, then either transform them so that they can satisfy this property. Otherwise, more sophisticated techniques are required. Also, determine the network configuration which the application will be running under. This is called the *input network configuration* (or input configuration). If

there is no profile associated with the input configuration, then either the protocol has to be run under this new configuration (and added to the library) or a profile exists in the library for a configuration that is close enough to the input configuration.

3. For a given input network configuration, determine a vector that best represents the application's requirements, i.e, determine a vector that captures the acceptable value boundary for each attribute. The boundary is the maximal or minimal acceptable value, depending on the attribute type. We refer to this vector as the *aspiration* vector.
4. For the given input network configuration, remove all vectors that are either dominated by the aspiration vector (i.e., all entries in the aspiration vector are better than the corresponding ones in the vector under consideration), since they fall short of the application's requirements for the input configuration.
5. If there are no candidates left, go to 3. Else, for each attribute, determine the minimum and maximum values from the remaining alternatives. This is done to help in determining normalized single-attribute functions (range from 0 to 1).

Step 2 - Characterization and Selection

1. Determine the (i) individual weights (or importance) of each attribute, (ii) individual relevance function and (iii) the overall relevance function.
2. For each algorithm (i.e., performance vector) in the set of remaining contenders, insert the attribute values in the overall relevance function to obtain their respective relevance or utility values.
3. Select the alternative with the highest relevance value.

We now explain the steps in more detail.

5.3. Step 1: Profiling and Filtering SLP-Aware Routing Algorithms

5.3.1. Profiling the Protocols

In the first phase of Step 1, we run every protocol under consideration under various network configurations. These profiles (or protocol performance vectors) can then be saved or stored in a protocol library that can be used whenever a new application is developed. This step need not be repeated for every application, but is a one-time activity. If a new protocol is developed, then the process is repeated for the new protocol, and its (normalized) performance profile is added to the library.

5.3.2. Determining Decision Attributes

We determine four decision attributes that could be classified into *gain* type (high value is better, e.g., delivery ratio) and *cost* type (high value is worse, e.g., capture ratio). Decision Attributes can differ depending on the applications:

- *Capture Ratio (cr)* is defined as the number of experiments ending in a capture of attacker in the safety period divided by the total number of experiment repeats for a specific parameter combination. The lower capture ratio is, the higher the source location privacy.
- *Delivery Ratio (dr)* is defined as the average percentage of messages send by the source that arrive at the sink across multiple simulation repeats.
- *Message Latency (lat)* is the average amount of time it takes a message to travel from the source to the sink.
- *Message Transmission (msg)* is the average number of messages transmitted through each node per second in the network. The attribute approximates the energy cost as sending and receiving are expensive activities in WSNs [1].

For a given network configuration c and given protocol $\mathcal{P}$, the result vector $r^{c,\mathcal{P}}$ can be determined experimentally (e.g., through simulations). The vector contains the recorded (raw) values of all decision attributes.

$$r^{c,\mathcal{P}} = (r_{cr}^{c,\mathcal{P}}, r_{dr}^{c,\mathcal{P}}, r_{lat}^{c,\mathcal{P}}, r_{msg}^{c,\mathcal{P}}) \tag{2}$$

Please note that, since our focus in this paper has been for SLP-awareness, the attributes of interest capture both SLP levels and WSNs performance (e.g., capture ratio, delivery ratio) and these are used in the vector. However, we conjecture that a similar heuristic can be used but for different objectives, requiring a different set of attributes.

An example of a result vector for an arbitrary SLP-aware protocol $\mathcal{P}^{'}$ for an input configuration c', using the above attributes, could be:

$$r^{c',P'} = (10\%, 90\%, 2500, 12800) \tag{3}$$

However, these attributes do not satisfy the mutually preferentially independent property. This is apparent as, for example, the capture ratio attribute is dependent on the delivery ratio attribute. For example, a low delivery ratio will imply a low capture ratio because the attacker will have overheard only a few messages and would not have been able to track the asset down. In a similar way, message transmission attribute is related to the delivery ratio in that, if a node does not receive a normal (data) message, then it is not going to forward it, reducing the number of message transmissions.

To address this issue, we opt to transform some of these attributes to attempt to introduce the mutual preferential independence property. Since delivery ratio is the one attribute that seems to affect both capture ratio and message transmissions, we normalize these two attributes with respect to delivery ratio, i.e., we penalize these attributes with respect to the delivery ratio. On the other hand, latency is independent of delivery ratio. Thus, we redefine the attributes as follows:

$$R_\omega^{c,\mathcal{P}} = \begin{cases} r_\omega^{c,\mathcal{P}} / r_{dr}^{c,\mathcal{P}} & \text{if } \omega \in \{cr, msg\}, \\ r_\omega^{c,\mathcal{P}} & \text{otherwise.} \end{cases} \tag{4}$$

5.3.3. Determining Aspiration Vector

With consideration of different scenarios, we choose the aspiration value for each attribute to remove any results not in the scope to meet the scenario requirement. The aspiration value defines the minimal (or maximal in the case of cost criterion) acceptable value for each attribute. We will denote the aspiration vector by μ_a.

5.3.4. Filtering the Protocols

Based on the performances of the various protocols, it is obvious that those protocols that are worse (in all attributes) than all other protocols can be removed from the list as it implies that such protocols will never get selected as there is always another protocol that can deliver better result. In our case, based on the selection of protocols that we have chosen, none of them is dominated and thus none of them gets removed from the list. For example, *ILP Routing-Max* has very low capture ratio but has very high latency as its mechanism is based on using time redundancy to achieve privacy.

5.3.5. Checking Remaining Values

For each attribute, we check whether any results are left in the scope of the aspiration value. If not, return to phase 3 and reselect the aspiration value as all remaining results do not satisfy the aspiration value.

5.4. Step 2: Characterization and Selection of SLP-Aware Routing Algorithms

5.4.1. Determining Weights and Utility Functions

In the first phase of step 2, we choose individual weight λ_ω ($\omega \in \{cr, dr, lat, msg\}$) which represents the importance of attributes. From step 1, having the aspiration vector, we use it to generate the utility function for each attribute. The total utility obtained by some algorithm is shown below, where $U_\omega^{c,\mathcal{P}}$ is single attribute utility and $R_\omega^{c,\mathcal{P}}$ is a result value in $R^{c,\mathcal{P}}$.

$$U^{c,\mathcal{P}}(\lambda_\omega, R_\omega^{c,\mathcal{P}}) = \sum \lambda_\omega \cdot U_\omega^{c,\mathcal{P}}(R_\omega^{c,\mathcal{P}}) \tag{5}$$

5.4.2. Inserting Attribute Values

In the second phase of step 2, for each attribute, we use utility functions and the remaining normalised result vector (i.e., performance vector) in the library as input to calculate the utility value. Then the final utility of algorithm under c can be calculated by Equation 5.

5.4.3. Selecting Utility Value

After proceeding above, we have obtained utility values of all algorithms and have choosen the best algorithm in terms of the highest utility value. In this case, we claim that under network configuration c and the given scenario, the algorithm with the highest utility value has the best performance.

6. Experimental Setup

In this section, we describe the simulation setup, parameters setup and safety period calculation that were used to generate the results (i.e., performance library), presented in Section 8.

6.1. Simulation Setup

The TOSSIM (V2.1.2) simulation environment was used in all experiments [42]. TOSSIM is a discrete event simulator capable of accurately modelling sensor nodes and the modes of communications between them. An experiment is made of a single execution of the simulation environment using a specified protocol configuration, network nodes and safety period. An experiment terminated when any source node had been captured by an attacker during the safety period or the safety period had expired.[1]

6.2. Parameters Setup

A square grid network layout of size $n \times n$ was used in all experiments, with $n \in \{11, 21\}$, i.e., networks with 121 and 441 nodes respectively. Source node generated messages and a single sink node collected messages. These nodes were assigned positions in the *SourceCorner* configuration from [10] where the source is in the corner and sink at the center of the grid. The rate at which messages from the real sources was generated was set to be 1 message per second. Nodes were placed 4.5 meters apart. At least 2000 repeats were performed for each combination of source location and parameters.

The node neighbourhoods were generated using two types of radio models. The first is ideal, which is a unit disk graph radio model (UDGM) where a perfectly reliable network link exists between the edges of a node's neighbours that are 4.5 meters away. The second is low-asymmetry, which uses the LinkLayerModel tool provided with TOSSIM to generate link strengths between nodes using the parameters shown in Table 3. Links generated with low-asymmetry have a small probability of becoming asynchronous.

The noise model was created using the first 2500 lines of `casino-lab.txt` and `meyer-heavy.txt`[2]. All the nodes are stationary (i.e., they do not move in the network).

[1] The source code for the algorithms tested and the scripts to run the experiments are available at `https://bitbucket.org/Chen_Gu/slp-algorithms-tinyos`.

[2] casino-lab.txt and meyer-heavy.txt are noise sample files provided with TOSSIM.

Number	casino-lab	casino-lab	meyer-heavy
of Nodes	ideal	low-asymmetry	low-asymmetry
121	12.64	9.87	22.89
441	25.42	20.06	46.84

Table 2: Time Taken for each network size when one message is sent per second.

Name	Value
PATH_LOSS_EXPONENT	4.7
SHADOWING_STANDARD_DEVIATION	3.2
D0	1.0
PL_D0	55.4
NOISE_FLOOR	-105
S	[0.9 -0.7; -0.7 1.2]
WHITE_GAUSSIAN_NOISE	4

Table 3: LinkLayerModel Parameters for the low-asymmetry radio model

6.2.1. Phantom Routing and Phantom Walkabouts

These two algorithms both rely on the random walk technique. When choosing the length of the short and long random walks, a variety of parameter combinations were considered. Our experiments set the short random walk series $S = \{2, 3, \ldots, 0.5 \times \Delta_{ss}\}$, and long random walk series $L = \{2 + \Delta_{ss}, 3 + \Delta_{ss}, \ldots, 1.5 \times \Delta_{ss}\}$, where Δ_{ss} is the sink source distance. In the phantom walkabouts, the short and long random walk length are randomly generated from S and L respectively. For phantom routing, we fix random walk length to be $0.5 \times \Delta_{ss}$ hops.

6.2.2. DynamicSPR

For this technique, as it aims to dynamically determine the parameters to use online, there are few parameters to specify. Other than the previously mentioned parameters, only the approach used needs to be specified. The approach determines how many fake messages are sent over the lifetime of a temporary fake source. There are three options: `Fixed1`, `Fixed2` and `Rnd`. `Fixed1` sends a single fake message over the duration, `Fixed2` sends two fake messages over the duration and `Rnd` sends either 1 or 2 messages randomly chosen.

6.2.3. ILP Routing

This algorithm has four parameters: the maximum walk length, the buffer size, the number of messages to group and the probability the message is sent directly to the sink. We use the same parameters as used in [39]. As the maximum walk length is simply to provide a finite bound in large networks, it was set to 100 hops. The number of messages to group was varied between {1, 2, 3, 4}. The buffer size was set to 10 messages as we do not expect more than 10 concurrent messages being sent in the network at one time. Finally, the probability of sending a message directly to the sink was set to 20% as it was identified as a good setting in the paper.

6.2.4. Protectionless Routing

We use two protectionless routing algorithms, namely flooding and Collection Tree Protocol (CTP). Flooding has been shown to provide no source location privacy. On the other hand, CTP is a convergecast type of protocol that collects data to be sent to the sink. Even though CTP keeps track of network information such as neighborhood information, to keep the routing reliable, the attacker cannot make use of this information as the relevance is only local. On the other hand, capturing a source required global information about the network.

6.3. Safety Period

A metric called the *safety period* (which we call *time-to-capture* from this point) was introduced in [7] which is the number of messages sent that an attacker needs to capture the source. The higher the time-to-capture is, the higher the source location privacy level. Using the time-to-capture metric means that simulation runtime is unbounded and potentially very large.

We thus use an alternative, but analogous, definition for safety period for each network size and network topology, we obtain the time-to-capture when protectionless flooding is used as the routing protocol. Flooding is used as it has been argued to provide the least SLP level, hence any SLP improvement is due to the SLP-aware technique [7]. The safety period is then obtained by increasing this value to account for the attacker potentially making bad moves. This definition is commensurate with [10, 26, 27, 35], but uses a different multiplicative factor due to the difference in the type of SLP technique being used.

Intuitively, the safety period captures the time period during which the asset will be at the same location. We calculate different safety periods *sp* as the following, where *tt* is the time-to-capture for protectionless flooding and ψ is the safety factor.

$$sp = \psi \times tt \quad \psi \in \{0.4, 0.8, 1.2, \ldots, 2.8\} \tag{6}$$

The time taken *tt* for each network size and network topology, for protectionless flooding is shown in table Table 2.

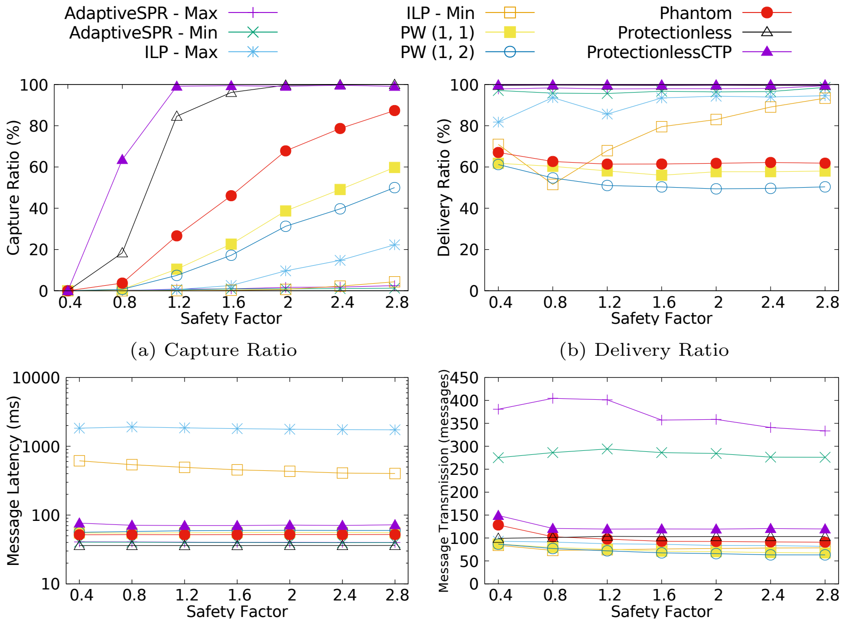
7. Example Execution of Decision Theoretic Procedure

In this section, we provide a brief example of the execution of the decision theoretic procedures we proposed during the *profiling and filtering* phase (Subsection 5.3) and the *selection* phase (Subsection 5.4).

Figure 1 is an example containing the results of the capture ratio, delivery ratio, latency and message transmission for the various protocols under consideration, with network configuration $c =$ (grid, 121, SourceCorner, CasinoLab, LowAsymmetry, 1.2) which specifies that the network is a grid network of 121 nodes (i.e., 11*11), *SourceCorner* topology (the source is at one corner of the grid), Casino Lab noise model, Low Asymmetry communication model and $1.2 \times tt$ safety period respectively. From Table 2, we can calculate that the actual safety period is 11.84 seconds. For simplicity, we only evaluate the overall utility of phantom routing and $PW(1, 1)$ for comparison for such a network configuration.

7.1. Step 1: Profiling and Filtering SLP-Aware Routing Algorithms

We now explain step 1 of the decision theoretic procedure.



(a) Capture Ratio

(b) Delivery Ratio

(c) Message Latency

(d) Message Transmission

Figure 1: Example: Multiple Algorithm Results

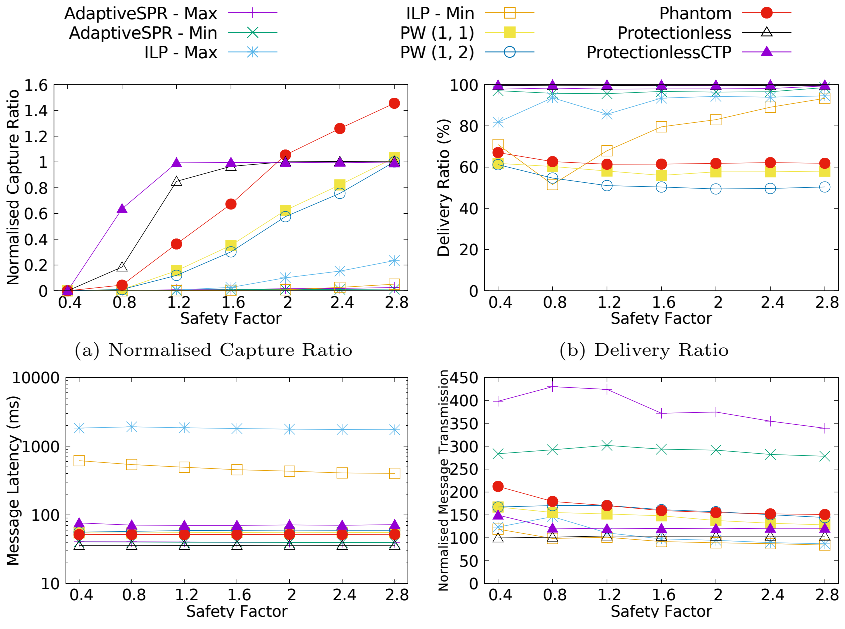
7.1.1. Profiling the Protocols

We execute a number of routing protocols, as explained in Section 6, some SLP-aware and others not. Figure 1 shows the graphs of capture ratio, delivery ratio, latency and message transmission.

Under configuration c (as above), the result vector of phantom routing is (0.25, 0.65, 0.05, 100), with 25% capture ratio, 65% delivery ratio, 50 ms for latency and 100 messages for message transmission. Similarly, the result vector of $PW(1,1)$ is (0.1, 0.6, 0.06, 75). As discussed in Subsubsection 5.3.2, results of attributes in the vector are not mutually preferentially independent, so need to be normalised in this case. The normalised results are shown in Figure 2. We calculate the normalised result vector of phantom routing, and is $(0.38, 0.65, 0.05, 153.85)$, while the normalised result vector of $PW(1,1)$ is $(0.17, 0.6, 0.06, 125)$. We use the normalised result vectors, or performance vectors, to form the protocol performance library, from which the most suitable SLP-aware protocol is to be selected. Since the objective here is to show the execution of our decision theoretic procedure, we focused on phantom routing and PW(1,1) as routing protocols.

7.1.2. Determining Decision Attributes

The four attributes we are interested in are: (i) capture ratio, (ii) delivery ratio, (iii) latency and (iv) message transmission or overhead. In general, for SLP, capture ratio and message or energy overhead are the two most important



(a) Normalised Capture Ratio

(b) Delivery Ratio

(c) Message Latency

(d) Normalised Message Transmission

Figure 2: Example: Multiple Algorithm Results of Normalised Capture Ratio and Message Transmission

overhead. However, there are applications when other parameters such as delivery ratio is important. In this paper, for the applications we consider, the above four attributes are considered relevant.

7.1.3. Determining Aspiration Vector

We now determine the aspiration value for each attribute. For instance, if 50% is given as a aspiration value for capture ratio and 60% for delivery ratio, the utility of capture ratio and delivery ratio will be set to 0 at these values. The system designer may consider that SLP cannot be provided if the capture ratio is greater than 50% and that the routing of protocol cannot work properly if the delivery ratio is lower than 60%. In this example, the aspiration vector is set to $(0.5, 0.5, 0.1, 250)$. This means that the normalized capture ratio is set to 50%, the delivery ratio is set to 50%, latency is set at 100 ms and the message overhead at 250.

7.1.4. Filtering the Protocols

Having the normalized results of both phantom routing and $PW(1,1)$, we first determine whether these two results are dominated by each other. If one protocol dominates the other, then there is a clear winner and the dominating protocol is selected as the best one. From our performance library, we observe that only the capture ratio and message transmission of $PW(1,1)$ perform better than phantom routing. Hence, we conclude that PW(1,1) does not dominate phantom routing and vice-versa. Therefore, in this case, we retain both for consideration.

7.1.5. Checking Remaining Values

Since neither PW(1,1) nor phantom routing dominate each other, we need to determine whether they are dominated by the aspiration vector. The aspiration vector is $(0.5, 0.5, 0.1, 250)$ while the performance profiles of phantom routing and PW(1,1) is $(0.38, 0.65, 0.05, 153.85)$ and $(0.17, 0.6, 0.06, 125)$ respectively. As can be observed, the aspiration vector does not dominate either of the protocols, hence both protocols are still under consideration.

7.2. Step 2: Characterization and Selection of algorithms

Since there is more than a single protocol still in contention, i.e., there is no clear winner, we now detail Step 2 to select the better protocol.

7.2.1. Determining Weights and Utility Functions

Based on the aspiration vector, we use sigmoid functions to build the utility functions for attributes[3]. We choose the parameters and generate the utility functions for the four attributes, as shown in Equation 7 to Equation 10. For simplicity, we adopt a weight vector with equal values $\lambda = (0.25, 0.25, 0.25, 0.25)$, meaning that all four attributes are equally as important.

$$U_{cr}^{c,\mathcal{P}}(R_{cr}^{c,\mathcal{P}}) = \frac{1}{1 + e^{10(R_{cr}^{c,\mathcal{P}} - 0.5)}} \tag{7}$$

$$U_{dr}^{c,\mathcal{P}}(R_{dr}^{c,\mathcal{P}}) = \frac{1}{1 + e^{10(-R_{dr}^{c,\mathcal{P}} + 0.5)}} \tag{8}$$

$$U_{lat}^{c,\mathcal{P}}(R_{lat}^{c,\mathcal{P}}) = \frac{1}{1 + e^{2(R_{lat}^{c,\mathcal{P}} - 1.5)}} \tag{9}$$

$$U_{msg}^{c,\mathcal{P}}(R_{msg}^{c,\mathcal{P}}) = \frac{1}{1 + e^{0.005(R_{msg}^{c,\mathcal{P}} - 1000)}} \tag{10}$$

7.2.2. Inserting Attribute Values

Using the utility functions identified (Equation 7 to Equation 10), we can calculate the utility value of each attribute in phantom routing: $U_{cr}^{c,\mathcal{P}}(0.38) = 0.76$, $U_{dr}^{c,\mathcal{P}}(0.65) = 0.82$, $U_{lat}^{c,\mathcal{P}}(0.05) = 0.95$ and $U_{msg}^{c,\mathcal{P}}(153.85) = 0.99$. Finally, using the identified weight vector λ, the final utility of protocol $\mathcal{P}$ phantom routing under c is:

$$\begin{aligned} U^{c,\mathcal{P}}(\lambda_\omega, R_\omega^{c,\mathcal{P}}) = \sum \lambda_\omega \cdot U_\omega^{c,\mathcal{P}}(R_\omega^{c,\mathcal{P}}) \\ = \;& 0.25 \times 0.76 + 0.25 \times 0.82 + 0.25 \times 0.95 + 0.25 \times 0.99 \\ = \;& 0.88 \end{aligned} \tag{11}$$

[3] Other utility functions could be also applied and we will show this in later sections.

Similarly, the utility value of $PW(1,1)$ also can be calculated: $U_{cr}^{c,\mathcal{P}}(0.17) = 0.96$, $U_{dr}^{c,\mathcal{P}}(0.6) = 0.73$, $U_{lat}^{c,\mathcal{P}}(0.06) = 0.95$ and $U_{msg}^{c,\mathcal{P}}(125) = 0.99$. The final utility is 0.91.

7.2.3. Selecting Utility Value

Comparing the final utility of phantom routing and $PW(1,1)$, we select $PW(1,1)$ as the better algorithm to provide SLP under a network configuration c and with weight λ, as it is the one with the highest utility value.

8. Case Studies: Routing Protocol Selection for Different Application Scenarios

In this section, we will develop three case studies to showcase both the applicability of, and the generality allowed by, our methodology. The three case studies we present are : (i) an animal protection scenario, (ii) a non-critical asset monitoring scenario and (iii) a security-critical military scenario.[4]

In the first phase, we reuse the library that has already been built, that consists of a number of protocols that have been profiled. We denote the library by $\mathbb{L}$ and the protocols are listed in Table 4. Next, we identified the set of decision attributes to consist of (i) capture ratio, (ii) delivery ratio, (iii) latency and (iv) message overhead.

In the next step, rather than deciding on the input network configuration, we will eschew this step so as to keep the discussion as general as possible. We also have the following aspiration vector:

$$\mu_a = (\min\{R_{cr}^{c,\mathcal{P}} \mid \mathcal{P} \in \mathbb{L}\}, \max\{R_{dr}^{c,\mathcal{P}} \mid \mathcal{P} \in \mathbb{L}\}, \min\{R_{lat}^{c,\mathcal{P}} \mid \mathcal{P} \in \mathbb{L}\}, \min\{R_{msg}^{c,\mathcal{P}} \mid \mathcal{P} \in \mathbb{L}\}) \quad (12)$$

Thus, this means that all protocols are in contention and will be under consideration, i.e., there is no filtering of protocols at this time.

The first phase of Step 2 is to decide the importance of each of the attributes (from capture ratio, delivery ratio, latency and message transmission) and to create a vector of weights quantifying the preference of each metric. Utilising the data and methods presented in Subsection 5.3, it is possible to calculate the utility of each protocol-parameter combination and generate plots to show which combination provides the highest utility for the given scenario. Specifically, using an input network configuration c, it is possible to then select the most appropriate protocol.

For attributes, we use both non-linear[5] and linear functions[6] to model the utility of each parameter, as shown in Table 5. For those important attributes, non-linear functions are used to satisfy the quick change rate of utility while linear functions are used for smooth change rate. Parameters for the different attribute utility functions in different scenarios are shown in Table 6.

[4] The dataset used to generated these results can be found at [43].

[5] We use sigmoid function with formula $f(x) = \frac{1}{1+e^{k(-x-x_0)}}$

[6] The formula is $f(x) = kx + x_0$

For all case studies, the network is assumed to be a grid with the source node assumed to be at the top-left corner (i.e., a SourceCorner configuration). Note that these need not be the case and there is no constraint imposed by the approach that precludes certain types of networks.

Algorithm Name	Technique	SLP-aware?
Protectionless	Flooding	No
Protectionless CTP	Collection Tree Protocol	No
DynamicSPR	Fake Messages	Yes
ILP Routing	Directed Walk	Yes
Phantom Routing	Directed Random Walk	Yes
Phantom Walkabouts	Directed Random Walk	Yes

Table 4: Algorithms Library ($\mathbb{L}$)

Attribute	Function Model Types		
	Animal Protection	Asset Monitor	Military
Normalised Capture Ratio	Non-Linear	Linear	Non-Linear
Delivery Ratio (%)	Linear	Non-Linear	Non-Linear
Latency (sec)	Linear	Linear	Non-Linear
Normalised Message Transmission	Linear	Non-Linear	Linear

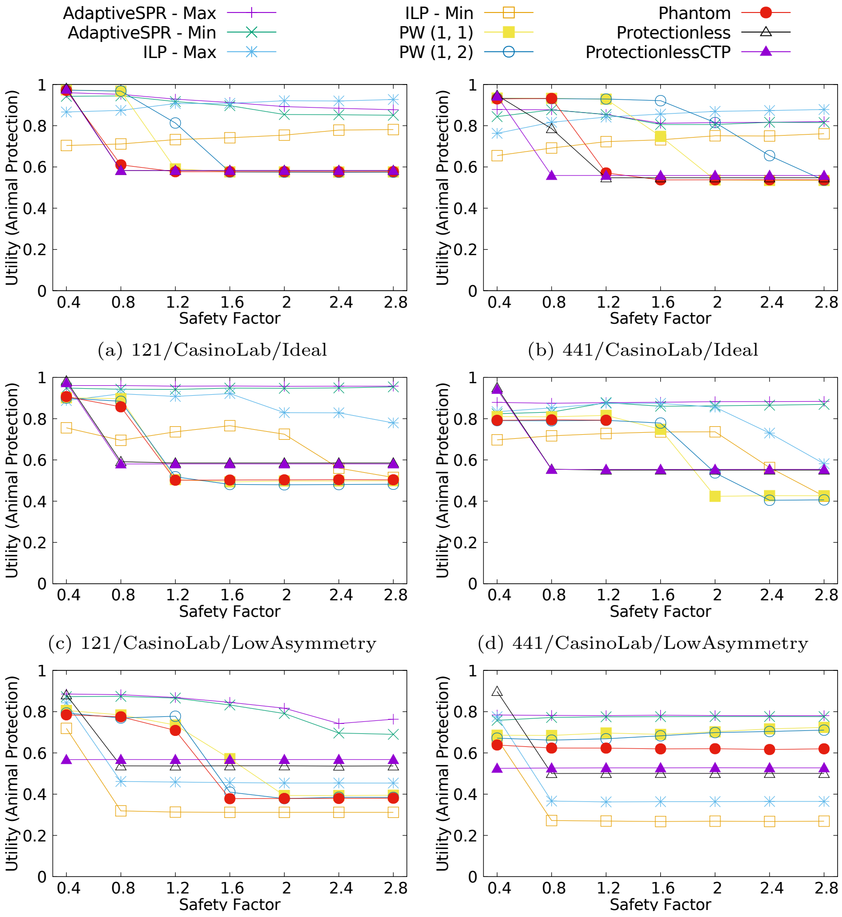
Table 5: Function Model Types

Attribute	Scenario								
	Animal Protection			Asset Monitoring			Military		
	k	x_0	weight	k	x_0	weight	k	x_0	weight
Normalised Capture Ratio	50.0	0.1	0.4	-1.0	1.0	0.2	50.0	0.1	0.4
Delivery Ratio (%)	1.0	0.0	0.2	20.0	-0.8	0.4	20.0	-0.8	0.25
Latency (sec)	-0.5	1.0	0.2	-0.5	1.0	0.1	10.0	0.5	0.25
Normalised Message Transmission	-0.0005	1.0	0.2	0.01	400	0.3	-0.0005	1.0	0.1

Table 6: Parameters for Attribute Utility Functions in Different Scenarios

8.1. Animal Protection Scenario

In this scenario, to prevent the rare animal from being captured by a poacher, SLP is crucial. Badgers protection [5] and the WWF's Wildlife Crime Technology Report [6] are real world examples of animal protection. Therefore, capture ratio is the most important attribute. To maximise network lifetime, the message overhead needs to be reduced while delivery ratio needs to be high as well to better understand the animal's behaviour. Thus, we set the weighting vector to be $\lambda = (0.4, 0.2, 0.2, 0.2)$. We then use these weights and the respective utility values (for each attribute, see Tables 5 and 6) to produce the overall utility plots,



(a) 121/CasinoLab/Ideal

(b) 441/CasinoLab/Ideal

(c) 121/CasinoLab/LowAsymmetry

(d) 441/CasinoLab/LowAsymmetry

(e) 121/MeyerHeavy/LowAsymmetry

(f) 441/MeyerHeavy/LowAsymmetry

Figure 3: Utility of Animal Protection Scenario

allowing us to deliberate on which protocol and parameter combination would be most suited for the application. Figure 3 shows the overall utility values generated using the weights and utility functions previously specified[7].

Protocol Selection: From the utility values, the input network configuration is required. For example, if the animal is expected to trigger a node that is at the top-left corner of a grid network of 11*11 that has been deployed and that the animal is expected to be constantly on the move (i.e., spend only a short time at a given location), and the environment is expected to be lightly noisy (i.e., similar to the Casino Lab noise model) and the links are expected to be often

[7] For simplicity, each configuration was described under corresponding graph with such format: number of nodes/noise model/communication model

unidirectional, then the input configuration can be as follows: c = (grid, 121, SourceCorner, CasinoLab, LowAsymmetry, 1.2). Then, this configuration will correspond to Figure 3c and the best protocol is AdaptiveSPR that AdaptiveSPR-Min and AdaptiveSPR-max provide near-comparable performance. On the other hand, for example, if the input configuration is c = (grid, 441, SourceCorner, CasinoLab, Ideal, 1.2), then the protocols that achieve the best trade-offs are PW(1,1) and PW(1,2) (see Figure 3b).

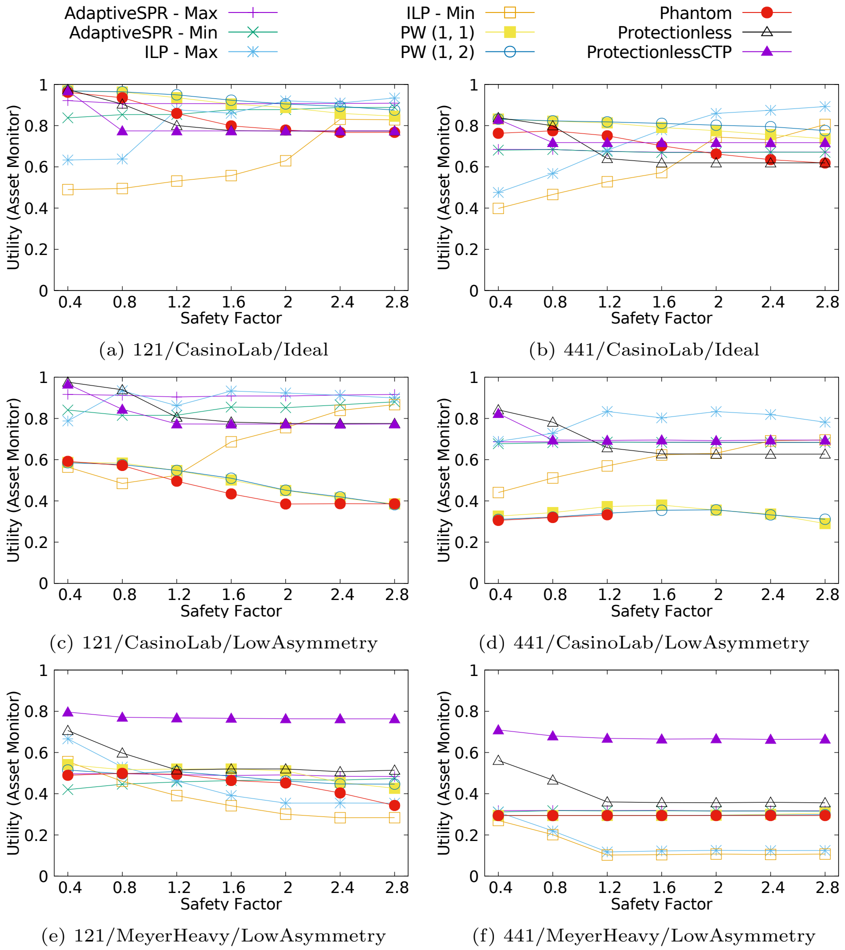
8.2. Asset Monitoring Scenario

Sensors are often deployed in the body of bridges or in a building to monitor product quality [2]. They can also be deployed to monitor and understand animal behaviour (e.g., Great Duck Island [1]), differently from animal protection, as explained in the previous section. For this type of application, it could be assumed that delivery ratio is the most important factor. This would leave capture ratio, latency and message transmission to be less important. Assume the weighting vector $\lambda = (0.2, 0.4, 0.1, 0.3)$ respectively representing capture ratio, delivery ratio, latency and message transmission.
Protocol Selection: From the utility values, the input network configuration is required. For example, if the animal is expected to trigger a node that is at the top-left corner of a grid network of 11*11 that has been deployed. Since the animal is not expected to be very mobile and the environment can be expected to be noisy (i.e., similar to the Meyer Heavy noise model) with unidirectional links due to a lack of line-of-sight transmission, then the input configuration can be as follows: c = (grid, 121, SourceCorner, MeyerHeavy, LowAsymmetry, 2). Then, this configuration will correspond to Figure 4e and the best protocol is Protectionless CTP.

On the other hand, if the environment is not very noisy, i.e., similar to the Casino Lab noise model, then with a network configuration c = (grid, 121, SourceCorner, CasinoLab, LowAsymmetry, 2), ILP Routing is the protocol that achieves the best trade-off Figure 4c.

8.3. Military Scenario

The use of sensor networks in military situations includes communication, battlefield surveillance and battle damage assessment among many others [2]. When these activities are carried out by military personnel, then SLP is extremely important. Further, these networks may be short-lived, thus message overhead is not very important. On the other hand, latency and delivery ratio are important, though less than SLP, to ensure soldiers can communicate in near real-time. Thus, the weight vector is $\lambda = (0.4, 0.25, 0.25, 0.1)$.
Protocol Selection: From the utility values, the input network configuration is required. For example, we assume that the surveillance activity to be carried out is expected to trigger a node that is at the top-left corner of a grid network of 11*11 that has been deployed. Since the personnel is expected to be very mobile and the environment can be expected to be noisy (i.e., similar to the MeyerHeavy noise model) with unidirectional links due to a lack of line-of-sight



(a) 121/CasinoLab/Ideal

(b) 441/CasinoLab/Ideal

(c) 121/CasinoLab/LowAsymmetry

(d) 441/CasinoLab/LowAsymmetry

(e) 121/MeyerHeavy/LowAsymmetry

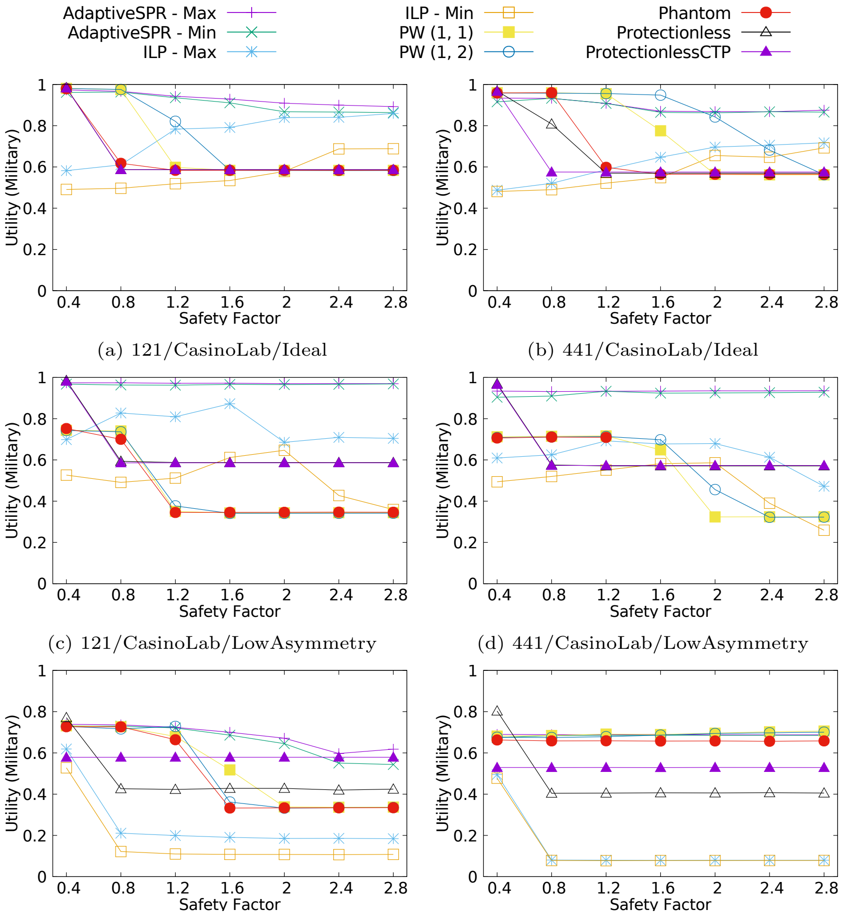
(f) 441/MeyerHeavy/LowAsymmetry

Figure 4: Utility of Asset Monitoring Scenario

transmission, then the input configuration can be as follows: c = (grid, 121, SourceCorner, MeyerHeavy, LowAsymmetry, 1.2). Then, this configuration will correspond to Figure 5e and the best protocol is AdaptiveSPR.

On the other hand, if the environment is not very noisy, i.e., similar to the Casino Lab noise model, then with a network configuration c = (grid,441, SourceCorner, CasinoLab, LowAsymmetry, 1.2), AdaptiveSPR is the protocol that achieves the best trade-off in Figure 5d.

In the ideal environment, apart from ILP Routing, other protocols are good choices. However, when the environment gets worse, Protectionless and ProtectionlessCTP generally become the protocols of choice.



(a) 121/CasinoLab/Ideal

(b) 441/CasinoLab/Ideal

(c) 121/CasinoLab/LowAsymmetry

(d) 441/CasinoLab/LowAsymmetry

(e) 121/MeyerHeavy/LowAsymmetry

(f) 441/MeyerHeavy/LowAsymmetry

Figure 5: Utility of Military Scenario

9. Conclusion and Future Work

In this paper, we propose a decision theoretic procedure for selecting the SLP-aware routing algorithm that achieves the best trade-offs among a set of attributes. The methodology is based on the existence of a library of performance profiles of the various routing algorithms and the decision theoretic procedure allows trade-offs to be assessed. This can be achieved when the attributes are mutually preferentially independent. The utility functions, the weights of the attributes and the network configurations are inputs that have to be provided by network administrators. We have presented three case studies to showcase the viability of the approach.

As future work, there are a few additions we plan on doing. First, we will focus on generating profiles for network configurations where the source is not located in the corner but rather at other locations in the network. We conjecture that specific protocols may have to be developed when the source is located elsewhere than the corner. Secondly, we will consider other protocols, such as OLSR [44], for protectionless routing to provide a baseline profile. And finally, we plan on investigating the suitability of preference learning [45] for selecting appropriate values for aspiration levels.

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