WARWICK
THE UNIVERSITY OF WARWICK

Manuscript version: Author's Accepted Manuscript
The version presented in WRAP is the author's accepted manuscript and may differ from the published version or Version of Record.

Persistent WRAP URL:
http://wrap.warwick.ac.uk/108762

How to cite:
Please refer to published version for the most recent bibliographic citation information. If a published version is known of, the repository item page linked to above, will contain details on accessing it.

Copyright and reuse:
The Warwick Research Archive Portal (WRAP) makes this work by researchers of the University of Warwick available open access under the following conditions.

© 2018 Elsevier. Licensed under the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International http://creativecommons.org/licenses/by-nc-nd/4.0/.

Publisher's statement:
Please refer to the repository item page, publisher's statement section, for further information.

For more information, please contact the WRAP Team at: wrap@warwick.ac.uk.

warwick.ac.uk/lib-publications

Towards Optimal Source Location Privacy-Aware TDMA Schedules in Wireless Sensor Networks

Jack Kirton[a,*], Matthew Bradbury[a], Arshad Jhumka[a]

[a] *Department of Computer Science, Univeristy of Warwick, Coventry, United Kingdom, CV4 7AL*

Abstract

Source Location Privacy (SLP) is becoming important for wireless sensor networks where the source of messages is kept hidden from an attacker. In this paper, we conjecture that similar traffic perturbation to altering the routing protocol can be achieved at the link layer through assignment of time slots to nodes. This paper presents a multi-objective optimisation problem where SLP, schedule latency and final attacker distance are criteria. We employ genetic algorithms to generate Pareto-optimal schedules using two fitness criteria, examining the Pareto efficiency of selecting either and confirming the efficiency by performing simulations which show a near optimal capture ratio.

Keywords: Genetic algorithm, Wireless Sensor Networks, TDMA, Data aggregation schedule, Source Location Privacy

---

1. Introduction

Wireless sensor networks (WSNs) have enabled novel classes of applications such as monitoring and tracking. Asset monitoring is a task performed by some WSNs, where some node(s) detects the presence of an asset and transmits data about the asset back through the network to a base station node known as the

*Corresponding author
Email addresses: `J.D.Kirton@warwick.ac.uk` (Jack Kirton), `M.Bradbury@warwick.ac.uk` (Matthew Bradbury), `H.A.Jhumka@warwick.ac.uk` (Arshad Jhumka)

sink. Even though sensitive data may be encrypted, the process of sending the message back to the sink, called *convergecast*, implicitly reveals the location of such an asset, as a potential attacker can trace back over the network traffic to the source of traffic, to ultimately capture the asset. *Source location privacy* (SLP) is the property of keeping the source's location within the network secret so as to prevent the capture of the asset.

The idea motivating this area of research was originally developed in [1, 2] as the panda hunter game. The panda hunter game is based upon the premise of using WSNs to monitor the population of endangered animals (in this case pandas) over a large area of their natural habitat, such as in [3, 4]. One of the typical problems facing endangered animals are poachers. While the data being transmitted through the network is encrypted (providing *content*-based privacy), the *context* in which the data is broadcast must also be protected. Context can be defined as a collection of attributes derived from the environmental and temporal situation in which the data was broadcast. This means that typical content-based privacy solutions (such as encryption) are not sufficient to solve context-based privacy issues. Hence, there is a need for context-specific privacy solutions.

The majority of existing work on SLP is focused on providing a solution at the *routing* layer of the network stack. In these works, the primary objective is to perturb the original (convergecast) routing protocol such that the resulting protocol (i) still routes data to the sink and (ii) the attacker cannot capture the source while backtracking on the network traffic. Based on the notion that traffic can be engineered to provide for SLP, we focus on achieving a similar objective while focusing at the link layer. Using the link layer as opposed to the routing layer has the advantage of typically sending less control messages [5] and as such reducing network energy consumption. Specifically, in WSNs, TDMA-based MAC protocols are often used in cases where timeliness is required. A TDMA-based MAC protocol works by splitting the timeline into slots and then allocating slots to nodes in such a way that message transmissions do not result in collision. Thus, it becomes possible to impose a given traffic pattern on the network based on slot allocation, providing a basis for traffic engineering at the link layer level. Specifically, each valid slot assignment for the network will provide a different pattern of traffic during operation. The principle then is that the slot assignment can be performed in such a way as to provide SLP within a class of convergecast protocol known as *data aggregation scheduling* (DAS). DAS works by constructing an aggregation tree rooted at the sink and the slot allocated to a parent is strictly greater than the slot of any of its children. Thus, a parent node will propagate aggregated information after collecting messages from all of its children.

Developing an optimal and valid TDMA schedule is known to be NP-complete [6]. However, we propose to add SLP as another optimization criterion in the design of optimal TDMA schedules. Our aim is thus to generate SLP-aware slot assignments utilising an evolutionary method in order to produce schedules that are valid for the network and also provide SLP.

We thus make the following contributions:

1. We map the SLP problem onto a GA problem.
2. We present suitable *crossover*, *mutation* and *selection* operators to expedite the generation of optimised schedules.
3. We use the notion of Pareto optimality to compare the various generated schedules and we use two different *fitness functions* for analysis.
4. We perform simulations in both ideal and realistic environments, showing metrics about the generated solutions such as near optimal capture ratio and high packet delivery ratio.

5. We examine those solutions that lie on the Pareto frontier and determine the optimal solution of those generated for a specific network configuration.

The remainder of the paper is organised into eight sections. Section 2 explores other works performed in this area. Section 3 provides models used during this work. Section 4 outlines the specification for DAS. The genetic algorithm and operators are detailed in Section 5. Section 6 defines Pareto efficiency and explains its utility. Section 7 explains the experiments that shall be run and the results are analysed in Section 8. Finally, Section 9 summarises our contributions.

2. Related Work

2.1. Source Location Privacy

Phantom routing was first introduced in [1, 2], alongside the the panda hunter game. Phantom routing is a two stage protocol, firstly transmitting the message from the source along a directed random walk to a phantom node and secondly using the routing protocol to continue the transmission to the sink. Two variants were proposed for altering the routing protocol in stage two; PRS [2] used flooding and PSRS [1] used single-path routing. There has been much work on providing SLP since [7].

Since the introduction of the phantom routing concept, more work has been created to improve the first stage of the protocol (i.e. the directed random walk). Two solutions that attempt to prevent the random walk from turning back on itself are GROW [8], which stores previously visited nodes in a bloom filter, and [9], which uses location angles. While some phantom routing work has focused on improving the selection of nodes that take part in the random walk [10], others have used delay to prevent the attacker making positive moves towards a source [11].

Several issues with Phantom Routing have been investigated. One such issue is the performance degradation associated with the use of multiple sources [12]. Another issue is that traffic-analysis of phantom routes that collide with the network boundary can allow prediction of the source's location [13].

An alternative technique utilises fake sources to misdirect the attacker. A fake source sends encrypted and padded messages that appear identical to those produced by a real source. The idea is to attract the attacker to one of the fake sources rather than the real one. A fake source technique was proposed in [1] but was deemed to have a poor performance and said that it was not worth investigating this class of solutions further. This was contested by [14], which implemented an alternative technique that provides high levels of SLP. This class of solution was further expanded in [15, 16] to make it applicable to a wider variety of areas and to determine parameters online. A drawback to utilising fake sources is that they often demand considerably higher energy usage than routing-based techniques.

Solutions exist that combine the use of both phantom routing and fake sources. [17] generates a routing tree where leaf nodes would be fake sources that send messages up the tree. A further example is fog routing [18] where the network is split into *fogs*, which creates routing loops that trap the attacker indefinitely. Within the fogs, fake sources are also used. PEM [19] generates fake sources that perform a walk about during execution.

The solutions presented thus far focused on the local (distributed) eavesdropper [20] where, at any point in time, the attacker only gathers information about its current neighbourhood and then moves to gain further information. A global attacker is a stronger attacker with a view of the entire sensor network. The attacker could either operate their own sensor network deployed over the target network [21] or use long range radios to eavesdrop on all traffic. Two solutions that provide perfect privacy against global attackers are Periodic Collection [22], where every node broadcasts periodically, and ProbRate/FitProbRate [23], where nodes broadcast periodically but the rate at which they do so is based on an exponential distribution.

Cross-layer techniques are those that employ more than one layer of the network stack to provide SLP. Typically, only the routing layer is used, as is the case for phantom routing, where a cross-layer solution would additionally employ another layer, typically the MAC/link layer. Cross-layer techniques are far less common than the others. In [24] beacon frames at the MAC layer are modified to carry data to aid in moving messages away from the source, in a similar fashion to phantom routing. After the message has been propagated far enough, a standard routing method is used to deliver the message to the sink. A second method was proposed whereby the message would first be routed to a *pivot* node on the first round of beaconing, sending the message further away on the second round before finally flooding to the sink. Another technique [5] employs SLP for TDMA DAS networks, where slot allocations are altered at the MAC protocol level in order to attract the attacker along a diversionary route.

Our solution can be considered a hybrid between the techniques that provide privacy against a global attacker and local attacker. The solution will have all nodes periodically broadcasting, but the pattern of broadcasts is done in such a way that a route is created for a local attacker to follow.

2.2. Genetic Algorithms

Genetic algorithms have been used for a wide variety of purposes in the sensor networks field. They have been used to find optimal parameters for routing protocols, such as LEACH [25], where it was used to determine weightings for combining multiple heuristics to determine which node became the next cluster head. The goal of this was to increase network lifetime by balancing energy loss between nodes more effectively. In [26], they went so far as to produce a new routing protocol created by a GA that is comparable to LEACH in order to use the least energy possible for those networks that harvest energy from the environment rather than batteries.

Genetic algorithms have also been used in the deployment of WSNs. The maximum coverage sensor deployment problem (MCSDP) is the problem of finding the minimum number of nodes required to cover a certain area [27]. Additionally, further work has been performed such that the deployment is augmented to find a solution that maximises the network lifetime by reducing energy requirements [28].

The allocation of TDMA time slots using genetic algorithm-related methods has previously been investigated [6, 29, 30] and finding an optimal TDMA schedule has been shown to be NP-complete [6]. So generating a TDMA schedule is a suitable problem for obtaining a near optimal result with GAs [31]. As the problem exists in NP, a benefit is that there exists a polynomial-time method of checking a solution's validity which is necessary as an efficient method is required for use as a fitness function.

A downside of GAs is that they typically run offline making it unsuitable for WSNs that determine a route online in response to changing conditions. Techniques such as network reprogramming can be used to update the TDMA schedule, but tend to be expensive in terms of energy. While some online GA implementations exist, due to a sensor node's limited resources, it is not feasible to employ these methods on this type of hardware.

3. Models

3.1. Network Model

A wireless sensor node (or node) is a device with a unique identifier that has limited computational capabilities. It has a wireless network interface that enables it to communicate directly with other nodes within its communication range. The set of nodes with which a given node n can directly communicate with is called the *neighbours* of n. We assume that all nodes in the network have the same communication range. There exists a distinguished node in the network called a *sink*, which is responsible for collecting data and which acts as a link between the WSN and the external world. Other nodes sense the presence of an asset and then route the data via normal messages along a computed route to the sink. We assume that any node can be a data source and only a single node is a data source at any time. We assume that the network is time-triggered, i.e., all node will periodically send a message to the sink, irrespective of whether it has sensed an asset.

We assume that nodes send ⟨Normal⟩ messages which are encrypted. The source node includes its ID in the encrypted message so that the sink can infer an asset's location; as we assume the network administrators will record where they put nodes. We do not assume that WSN nodes have access to GPS due to the resulting increase in energy cost.

3.2. Attacker Model

The authors of [20] presented a taxonomy attacker strength for WSNs and show that it could be factored along two dimensions, namely *presence* and *actions*. Presence captures the network coverage of the attacker, while actions capture the attacks the attacker can launch. For example, presence could be local, distributed or global, while actions could be eavesdropping or reprogramming among others.

In this taxonomy, the attacker we assume is a *(mobile) distributed eavesdropper* based on the patient adversary, introduced in [1]. Such an attacker is reactive in nature and executes the following steps:

1. **Start:** The attacker initially starts at the sink.
2. **Update:** When the attacker is co-located at a node n and receives (i.e., overhears) a message that it has not been received before[1], from a neighbour node m, the attacker will move to m. Thus, in a normal setting, the attacker is geared to moving closer to the source as he only follows unique messages.
3. **End:** Once the source has been found, the attacker will no longer move.

Most often, the attacker will execute the *Update* step. Repeating this action for a number of times may enable the attacker to capture the asset as the attacker performs a traceback on the traffic flow to the asset. We assume that the attacker has the capability to perfectly detect which direction a message arrived from, that it has the same radio range as the nodes in the network, and also has a large amount of memory to keep track of information such as messages that have been heard. This is commensurate with the attacker model used in [5].

3.3. Safety Period Model

The overall objective of any WSN-based SLP solution is to ensure that the asset (at a specific location) is *never* captured through the WSN and the attacker is instead required to perform an exhaustive search. However, two issues arise: (i) if the asset is not mobile, then the attacker can take as long as it requires to perform an exhaustive search of the network, which makes providing SLP in this case irrelevant. (ii) On the other hand, if the asset is mobile, then performing an exhaustive search of the network is unsuitable as the attacker may approach

[1]Previous work [1] has assumed that the attacker has the ability to identify whether a message has been previously responded to and we also make this assumption

a given location after some considerable time only to find out that the asset has moved. If the asset is mobile, which we assume, but spends a long time in a single location, then we do not consider the asset to be mobile. Thus, the SLP problem can only be considered when it is *time-bounded*, i.e, when the asset has to be captured within a given time window.

This notion of time bound has been termed as *safety period* in the literature. The aim of SLP techniques is to either to maximise the safety period, i.e., the higher the time to capture, the higher the SLP level provided [1]. Or to reduce capture within this time window.

3.4. Routing Protocol

In WSNs, a routing protocol is required to transfer data from a source node to the sink node. The routing protocol is considered to be a set of paths that end at the sink. A message will travel along at least one of the paths to the sink. A message may follow the same path as previous messages to the sink or it may follow a different path. The routing protocol we assume in this paper is flooding where every message will follow all the possible paths to the sink.

4. DAS Problem Specification

Data aggregation scheduling (DAS) is a type of convergecast protocol where each parent node receives information from *all* of its children before broadcasting an aggregated message. DAS is defined as a series of conditions [5], as follows:

1. A node can only be allocated one time slot in which to broadcast.
2. All nodes, excluding the sink, will be allocated at least one time slot. With condition 1, this means that each node will receive exactly one time slot to broadcast in.

3. Whenever a node broadcasts a message, *at least one* of its neighbours closer to the sink will transmit in a later slot. One of the neighbour nodes that broadcast later will be this node's parent.
4. The schedule will be collision-free. This requires that nodes within the same collision group (i.e. two-hop neighbourhood) must have unique time slots.

5. Genetic Algorithm

5.1. Algorithm

The algorithm selected for this work is the generic and standard genetic algorithm using non-standard and optimised genetic operators for the problem domain. One reason for this selection is so that we can build a genetic algorithm to our own required specification and optimise for the SLP problem. Another reason is that [32] finds that using a scalar combination of fitness scores speeds up computation over using a multi-objective algorithm, at the disadvantage of being unable to discover concave Pareto fronts. We do not expect the Pareto front to be concave in this instance and as such do not suffer from this disadvantage. However, we also examine the usage of a more advanced, true multi-objective GA, NSGA-II [33], as a comparison.

5.2. Genome Representation

For this problem, the representation must contain a graph $G = (V, E)$, where E is the set of edges between nodes in V who are within communication range. Each node in V is also labelled with a slot value, the number of hops from the sink, a parent node and a set of child nodes.

The reason that this representation differs from that used by [6] is that it is incapable of portraying the additional constraints required by DAS, so a full graph representation must be used instead.

5.3. Genetic Operators

As described in [6], providing operators with a context of the problem domain and forcing the creation of valid solutions after each operator's function can aid in providing better solutions using less generations at a performance cost at each step. The operators described below each produce genomes that are valid DAS solutions.

5.3.1. Initialisation

The initialisation function is required to create an individual to be included in the initial population.

Algorithm 1 performs the network initialisation. Within the algorithm, the first stage is to initialise all attributes of each node with sensible defaults. The parameter *maxSlots* is used to provide a number of *pseudo slots* for the genetic algorithm to assign during operation. Providing a number too large will result in more slot values being different (thus more slots used in the final solution) where providing too few will result in the genetic algorithm struggling to find a solution. In the final solutions, all pseudo slot values are normalised to their minimum range. The next stage creates a DAS parent-child tree from the nodes, changing slot values to ensure the genome conforms to the DAS specification. The function, SetParent, sets a node's parent and also adds the node to the parent's *children* set.

5.3.2. Crossover

The crossover operator is used to combine two parent individuals together to create two children which incorporate features from both parents.

The crossover operation is contained within three functions in Algorithm 2: Crossover, OneCrossover and CheckCrossover. Crossover is a wrapper function that simply selects the node which will be the head of the crossover

Algorithm 1 Algorithm for initialising a genome

```
    ▷ g: genome, sink: sink node, maxSlots: number of pseudo slots
function Initialise(g, sink, maxSlots)
    ▷ First initialise all nodes with some values
    for all node ∈ g do
        if node = sink then node.slot := maxSlots
        else node.slot := RandomInteger(1, maxSlots − 1)
        node.hop := ShortestPathLength(g, node, sink)
        node.parent := ⊥
        node.children := ∅
    repeat := 1
    while repeat do
        repeat := 0
        ▷ Assign a parent to each node without one
        for all node ∈ {n | n ∈ g \ {sink} ∧ n.parent = ⊥} do
            slotChanged := 0
            parentChoice := GetPotentialParents(g, node)
            SetParent(g, node, Choose(parentChoice))
            if node.slot ≥ node.parent.slot then
                node.slot := node.parent.slot − 1
                slotChanged := 1
            ▷ Resolve collisions
            nhs := GetTwoHopNeighbourhoodSlots(g, node)
            while node.slot ∈ nhs do
                node.slot := node.slot − 1
                slotChanged := 1
            if slotChanged then
                for all c ∈ node.children do
                    SetParent(g, node, ⊥)
                    repeat := 1
    return g
```

and returns the product of performing crossover for each child. OneCrossover gets the subnetwork that is being introduced to the child and overwrites those elements in the new child genome. CheckCrossover is where any issues pertaining to the validity of DAS get resolved, by starting at the crossover node and recursing through all descendents.

Figure 1 shows an example execution of this method. Starting with a father and mother genome, the algorithm begins by selecting the crossover node, which in this case is at the coordinates $(4, 4)$. Then, the DAS parent-child tree structure from the father is transplanted into a clone of the mother solution (the daughter) and the same occurs for the mother to the father (creating the son). The slot values and the DAS structure can then be altered to ensure DAS validity remains

Algorithm 2 Crossover two genomes

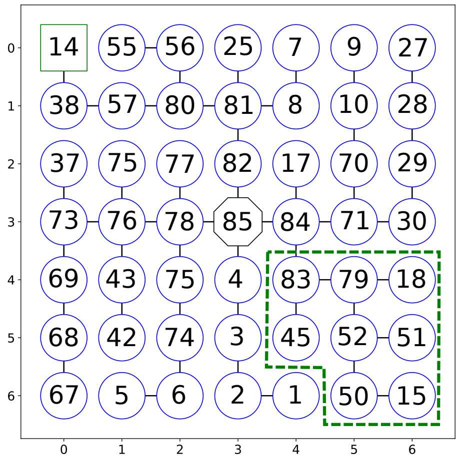
```
    ▷ father: father genome, mother: mother genome, sink: sink node
function Crossover(father, mother, sink)
    son, daughter := father, mother
    crossoverNode := Choose(father \ {sink})
    son := OneCrossover(son, mother, crossoverNode)
    daughter := OneCrossover(daughter, father, crossoverNode)
    return son, daughter

function OneCrossover(g1, g2, crossoverNode)
    subnetwork := GetDescendents(g2, crossoverNode)
    for all node ∈ subnetwork do
        g1[node].slot := g2[node].slot
        if g2[node].parent ∈ subnetwork then
            SetParent(g1, node, g2[node].parent)
        else                                        ▷ This occurs with the crossoverNode
            SetParent(g1, node, ⊥)
    CheckCrossover(g1, crossoverNode)
    return g1

function CheckCrossover(g, node)
    if g[node].parent = ⊥ then
        parentChoice := GetPotentialParents(genome, node)
        SetParent(g, node,Choose(parentChoice))
    if g[node].slot > g[node].parent.slot then
        g[node].slot := g[node].parent.slot
    nhs := GetTwoHopNeighbourhoodSlots(g, node)
    while g[node].slot ∈ nhs do
        g[node].slot := g[node].slot − 1
    for all child ∈ g[node].children do
        CheckCrossover(g, child)
```

in the child genomes.

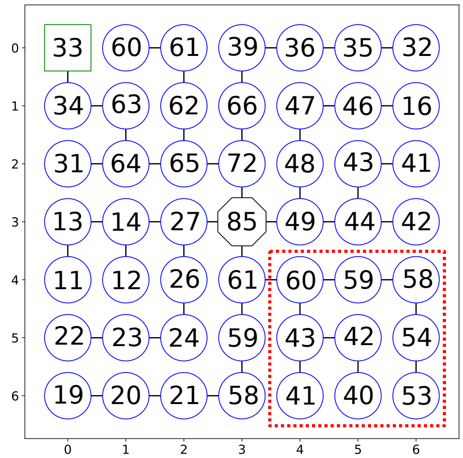
5.3.3. Mutation

The mutation operator is an attempt to further introduce diversity into the population to prevent stagnation.

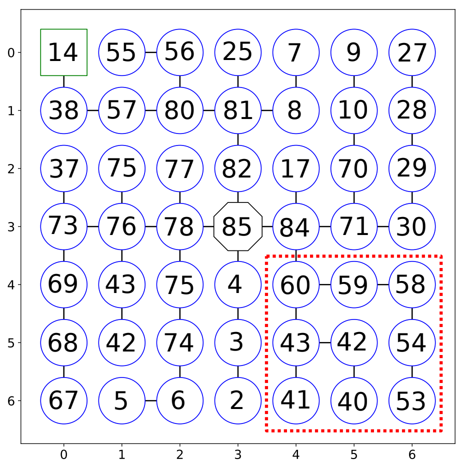
Algorithm 3 begins by defining a range in which the new slot value should be chosen. The $maxDiff$ parameter denotes the maximum range in which a slot value can be altered. Should the node have no children, the slot value is reduced by one, which repeats should there be a slot collision in the two-hop neighbourhood. The reason for this is to prevent a large variety of different slot values at the edges of the network. Otherwise, the low end of the slot range is



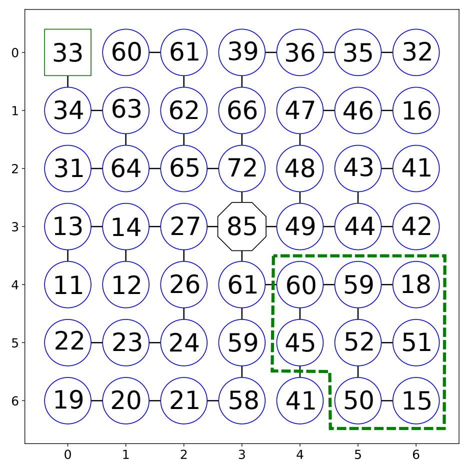
(a) Father genome



(b) Mother genome



(c) Son genome



(d) Daughter genome

Figure 1: An example of performing crossover at node $(4, 4)$

refined to be within the acceptable range that the children of the node set (i.e. a parent node cannot have a lower slot value than its children). A new slot is then attempted to be randomly selected (avoiding slot collisions) subject to the parameter *attempts* which limits the number of times this is tried before exiting with failure.

Figure 2 shows an example of the algorithm in operation. For the example, the mutation rate is set to 10%, which is too high for normal operation but

Algorithm 3 Randomly alter slot values within DAS constraints

```
    ▷ g: genome, node: node to mutate
    ▷ maxDiff: the maximum range of values to select new slot from
    ▷ attempts: the number of attempts to make at mutating the slot
function MUTATE(g, node, maxDiff, attempts)
    highest, lowest := node.parent.slot, highest − maxDiff
    nhs := GETTWOHOPNEIGHBOURHOODSLOTS(g, node)
    if node.children = ∅ then
        node.slot := highest − 1
        while node.slot ∈ nhs do
            node.slot := node.slot − 1
    else
        for all child ∈ node.children do
            if child.slot > lowest then
                lowest := child.slot
        while attempts > 0 do                ▷ If attempts reaches zero, mutation failed
            newSlot := RANDOMINTEGER(lowest + 1, highest − 1)
            if newSlot ∉ neighbourhoodSlots then
                node.slot := newSlot
                break
            else
                attempts := attempts − 1
```

useful to see the effect of the operator. All cases of the algorithm can be seen, such as nodes with no children being reduced minimally, nodes with children that have a range of slots to select from and finally nodes that have children but failed to change slot.

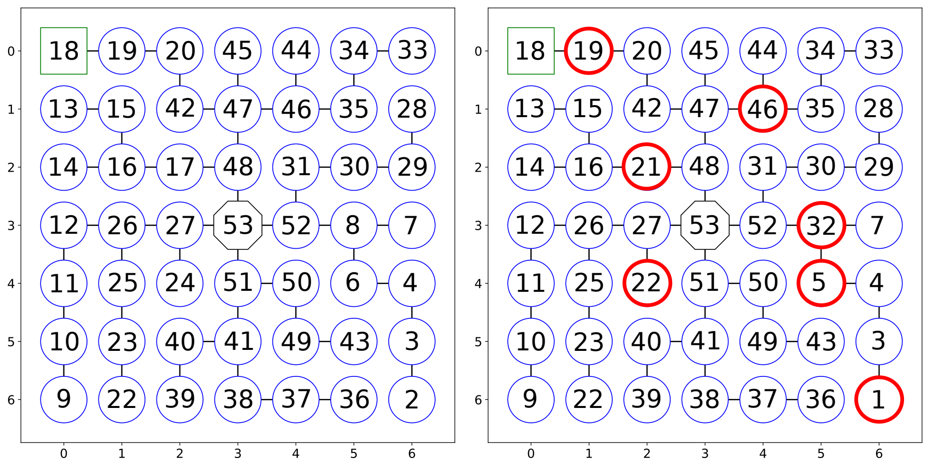
5.3.4. Selection

The selection operator is used to select solutions from the new population to be entered into the next generation.

In this work we shall use standard tournament selection where the number of solutions in each tournament is 2. Algorithm 4 shows the tournament selection method for a variable value of the number of solutions per tournament, t.

5.4. Fitness Functions

The fitness function is used to assign a numerical *worth* to each individual in the population based upon its perceived quality. This score is then used by the selection operator in order to choose the best individuals for crossover and mutation.



(a) Before mutation (b) After mutation

Figure 2: An example mutation using Algorithm 3

Algorithm 4 Select an individual from the population using tournament selection

▷ *pop*: population, t: number of genomes to compete in each tournament

function SELECT(pop, t)
  $best := pop[\text{RANDOMINTEGER}(0, pop.size)]$
  if $t = 1$ **then return** $best$
  for $i := 2 \rightarrow t$ **do**
    $next := pop[\text{RANDOMINTEGER}(0, pop.size)]$
    if FITNESS($next$) $>$ FITNESS($best$) **then** $best := next$
  return $best$

In this work we shall examine results from two different fitness functions. Algorithm 5 shows the first fitness function, which simply provides a value in the range $[0, 1]$ depending on the total number of slots used to generate the solution, where 0 would be given if each node had its own time slot (the worst case) and 1 if each node had the same slot, which is not possible due to the DAS constraints. Therefore, the best achievable score for this function is unknown. Additionally, the function returns 0 if the attacker path intersects the source, as the solution does not provide SLP.

The second function (Algorithm 6) performs the same as the first with the additional optimisation of making the attacker move as far away from the source

Algorithm 5 Slot usage fitness

▷ g: genome, src: source node
function SlotUsageFitness(g, src)
  if $src \in$ AttackerPath(g) **then return** 0
  $uniqueSlots := \{node.slot \mid node \in g\}$
  return $(|g| - |uniqueSlots|)\ /\ |g|$

Algorithm 6 Distance from source and slot usage fitness

▷ g: genome, $source$: source node
▷ w: the weighting for attacker paths end points distance to the source
function DistAndSlotUsageFitness(g, src, w)
  if $src \in$ AttackerPath(g) **then return** 0
  $endNode :=$ AttackerPathEnd(g)
  $dist :=$ ShortestPathLength($g, src, endNode$)
  $diameter :=$ NetworkDiameter(g)
  $distScore := w \times (dist\ /\ diameter)$
  $slotScore := (1 - w) \times$ SlotUsageFitness(g, src)
  return $distScore + slotScore$

as possible. With the first function, the attacker path can be liable to take the attacker closer to the source. This is undesirable, as in the case of link failures and node crashes along the path that we wish the attacker to take, the attacker could leave the predicted path and travel to the source, thus capturing the asset. In this work we shall only be examining the occurrence of link failures due to noise on the wireless channel. This function also provides a value in the range $[0, 1]$, with 1 being scored if the path leads the attacker as far away as allowed by the network. By using the parameter w we provide a weighting to the further distance aspect over the regular total slot reduction. In this work, $w = 0.25$, meaning that slot usage is weighted at 75% and the distance is weighted 25% of the total fitness score returned.

The reason for comparing two fitness functions is that the second provides a better solution in an unreliable network, but it is unknown how this will affect the slot usage reduction process.

6. Pareto Efficiency

After running the genetic algorithm, multiple competing solutions will be generated. Since we are concerned with maximising the level of source location privacy while minimising the number of slots and maximising the path distance between a source and the end point of an attacker, this search process is a multi-objective optimisation process. As such, no universal definition of an optimum can be given. One solution for an appropriate definition of optimality in multi-objective optimization was given by Vilfredo Pareto in 1896. This definition expresses that a solution is *Pareto-optimal* if there exists no other feasible solution which would decrease some objective without causing a simultaneous increase in at least one other objective [34].

More formally, consider a set of n solutions $s_i \dots s_n$, with a solution s_i being a vector of m attributes, i.e., $s_i = \langle a_i^1 \dots a_i^m \rangle, a_i^j \in \mathcal{R}$. A solution s_i is Pareto-optimal if there is no other feasible solution s_j where $j \neq i$ such that, for a given set of m utility functions $U_1 \dots U_m$, $\langle U_1(a_j^1), \dots, U_m(a_j^m) \rangle \geq \langle U_1(a_i^1), \dots, U_m(a_i^m) \rangle$ with at least one attribute a_j^k such that $U_k(a_j^k) > U_k(a_i^k)$. On the other hand, if such a solution s_j exists, then we say that s_j is a Pareto improvement on s_i.

Given a set of feasible solutions (and a way of valuing them), the *Pareto frontier* is the set of choices that are Pareto efficient. Formally, given a solution space $\mathcal{S}$, the Pareto frontier of S, denoted by $P(\mathcal{S})$ is $P(\mathcal{S}) = \{s \in \mathcal{S} | \forall s' \in \mathcal{S}$ s.t s' is not a Pareto improvement on $s\}$.

Using Pareto dominance allows a comparison of many solutions, where one can easily analyse the tradeoffs between selecting any one solution compared with another.

7. Experimental Setup

In this section we describe the environment and methods used to generate the results in Section 8. This genetic algorithm[2] was implemented using Python, the Pyevolve genetic algorithm framework [35], and the graphing library NetworkX [36]. We also attempted to utilise an implementation of the multi-objective genetic algorithm NSGA-II [33].

7.1. Network Configuration

To test the genetic algorithm and subsequently use these solutions in simulations, the simplest configuration for the network is an 11×11 square grid of nodes (121 nodes). The separation distance between each node is such that nodes can communicate vertically and horizontally but not diagonally. The source will be placed in the top-left corner while the sink will be placed in the centre.

A total of 100 solutions per fitness function (for a total of 200) will be created by the genetic algorithm. Each of these will have a unique slot assignment compared with the others, providing a different operating scenario between each solution. To gather results about the efficacy and efficiency of the solutions, approximately 600 runs of each solution will be performed in the simulator each for two different communication models, providing a total of $240,000$ simulation runs.

7.2. Genetic Algorithm Parameters

The main parameters for a genetic algorithm are *elitism*, *crossover rate*, *mutation rate*, *population size* and *total generations*.

Elitism is the number of copies of the best solution from the previous generation that should be entered into the next generation unaltered (i.e. no crossover

[2]The source code for the genetic algorithm can be found at `https://bitbucket.org/jack-kirton/slp-tdma-das-genetic`

or mutation). A value of 1 was chosen for this parameter as taking a single copy of the best solution from the previous generation to the next allows for the genetic algorithm terminating, ensuring that at least one solution that is supposedly good is available to present at the end of the algorithm.

The values of crossover rate, mutation rate and population size are set to the Pyevolve defaults of 90%, 2% and 80 respectively. The values chosen for parameters are sensible defaults. Finding the most optimal parameter configuration is left as an exercise for future work. Total generations for this work is capped at 200, which was shown through testing to be a reasonable compromise between time taken and quality of result. For results that optimise each fitness score further, more generations can be used at the cost of time.

7.3. Simulation & Algorithm Parameters

The WSN simulation environment that is used in this work is TOSSIM, TinyOS's (version 2.1.2) own discrete event network simulator[3]. Two communication models are compared, the first being an *ideal* model which sets a fixed signal receive strength when in range, making it almost 100% reliable. The second, named *low-asymmetry*, is generated using the LinkLayerModel provided with TinyOS and the parameters shown in Table 1. Low-asymmetry gives the simulation a small probability of packet losses and links becoming unidirectional, more akin to a real-world application. The noise model used is the first 2500 lines of the casino-lab noise file provided with TinyOS.

Most parameters for the algorithm are provided by the generated genetic algorithm solution (i.e. number of slots). Two that are not provided are the dissemination and slot period lengths. These values were set to 0.5 seconds and 0.1 seconds respectively. During the simulation, no data will be transmitted

[3]The source code for the implementation using TinyOS is available at `https://bitbucket.org/jack-kirton/slp-algorithms-tinyos`

Table 1: Low-Asymmetry LinkLayerModel Parameters

Name	**Value**
PATH_LOSS_EXPONENT	4.7
SHADOWING_STD_DEV	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

in the dissemination period as all nodes are aware of the data they require at compile time. Time synchronisation would normally be used in this period but this is not modelled by the simulator. Given the number of slots and the dissemination/slot periods we can calculate the rate at which the source sends messages (the source period) as we wish for the source to send a single message per TDMA period.

A safety period (the length of time we believe we can protect the source from capture) is also provided. We state that the time taken to reach the source in a protectionless TDMA DAS environment is $periodLength \times (\Delta\,(Sink - Source) + 1)$, where $\Delta\,(Sink - Source)$ is the number of hops between the sink and source, as this is the time it would take for the attacker to travel one of the shortest paths to the source. Therefore, we selected an upper bound of $periodLength \times (\Delta\,(Sink - Source) + 1) \times 2$. The reasoning behind this value is that if the attacker has not reached the source within a factor of 2x that of the shortest path then it is trapped somewhere in the network, unable to reach the source.

7.4. Experiments

We will examine four metrics from the TOSSIM simulations: messages sent, capture ratio, message receive ratio and latency. A comparison will be made between combinations of fitness function and communication model for each solution produced by the GA.

We expect the number messages sent to be similar across all solutions. There will likely exist variation between solutions depending on the total number of slots utilised, as this implicitly defines the length of a TDMA period. Better slot utilisation will result in a quicker TDMA period, resulting in a higher message send rate.

Capture ratio should be 0% for both fitness functions with the ideal communication model. This is because there should be no radio interference causing the attacker to leave the predicted path. However, with the low-asymmetry communication model, because of the noise and varying link qualities, both fitness functions should show varying capture ratios. Between the two fitness functions, it is expected that the slot usage fitness function will have more solutions of a higher capture ratio than that of slot usage and path distance.

Message received ratio is the percentage of normal messages sent by the source that were received by the sink. The message received ratio should be close to 100% for the ideal communication model due to perfect link quality, whereas low-asymmetry will provide slightly less.

Latency is the amount of time taken for normal messages sent by the source to reach the sink. We expect that the messages will travel from source to sink in a maximum time of the TDMA period (excluding the dissemination period). This is due to the design of DAS, where messages should be able to travel from any point in the network to the sink in a single period due to the path of increasing slot assignments.

Those solutions selected from the Pareto frontier will be examined in further detail, finally determining the optimal solution for the configuration.

8. Results

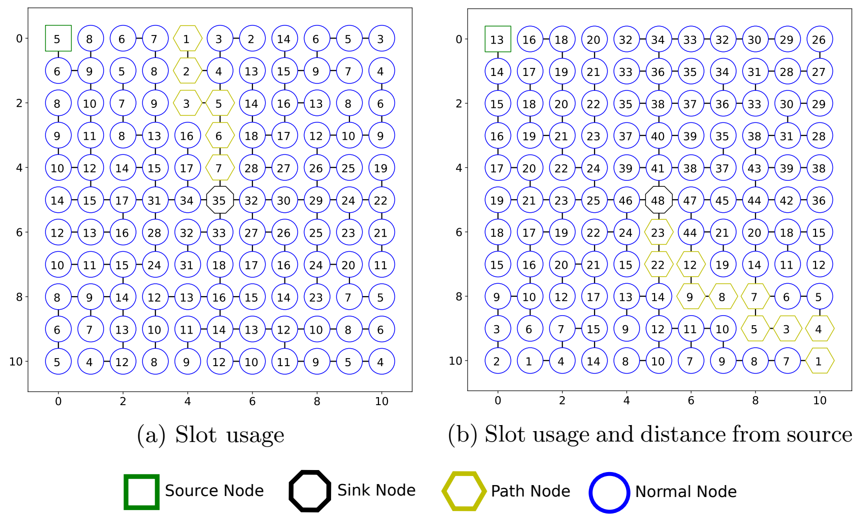
8.1. Genetic Algorithm

Figure 3 shows two example solutions produced by the GA, each using a different fitness function. Figure 3a shows a solution using the standard slot usage fitness function and Figure 3b shows a solution using slot usage and optimising the attacker path end's distance from the source.

In both examples contained in Figure 3, blue circles are normal nodes with the source node being labelled as a green square in the top left and the sink node being placed in the centre as a black octagon. The yellow hexagons are the nodes that the GA has predicted the attacker will follow through the network, known as path nodes. The reason that the attacker will follow this path is that each next node in the path has the lowest slot assignment in the surrounding one-hop neighbourhood, which means the attacker will hear from that node before any others. The connecting lines between the nodes show the DAS parent-child hierarchy, which is a tree structure rooted at the sink node. As previously stated, to ensure DAS-compliance, each node (bar the sink node) must have a parent that has a higher slot than itself and the connecting lines show that DAS has been preserved.

What isn't shown clearly by the examples is that the GA produces attacker paths that cause the attacker to oscillate between the end two nodes of the path indefinitely. This is because each of the two nodes at the end of the path has the lowest slot in the one-hop neighbourhood surrounding the attacker.

Examining the attacker paths visually, the difference between the two fitness functions can clearly be seen. As expected, including an optimisation to have the attacker travel as far away from the source as possible has caused the genetic algorithm to produce solutions that do just that, forcing the attacker into the opposite corner of the network (or thereabouts).



(a) Slot usage

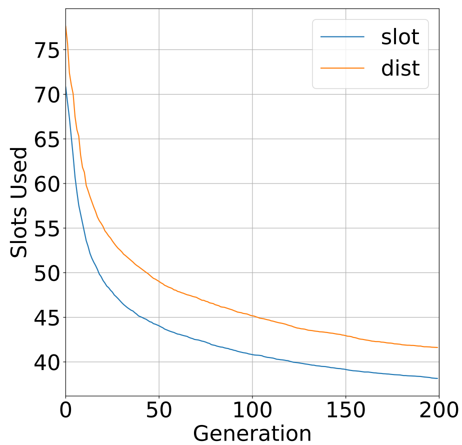
(b) Slot usage and distance from source

Figure 3: Example solutions produced by the GA using different fitness functions

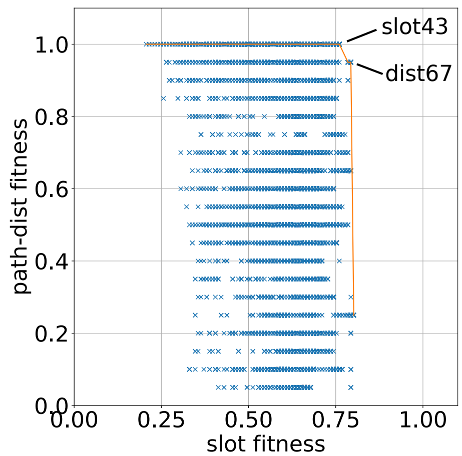
Figure 4a shows the cost of the additional fitness constraint, where *slot* is the original fitness function and *dist* is the function with the distance constraint. The plot shows generations against the number of slots used by the best candidate of that generation. The plot was produced using averages from 100 runs of each fitness function. This plot shows that there is an increase in the number of slots required to support the additional distance optimisation. However, the difference in total slots used is still a small value, although this would rise on more connected networks with larger numbers of nodes.

8.2. Pareto Efficiency

Figure 4b shows a plot of solutions comparing the slot usage and path distance fitness functions. Each point on the plot shows solutions at various generations. The Pareto frontier can be seen as the maximal boundary over all of the solutions. The plot shows that solutions can easily maximise the path distance fitness function, which is intentional as the path distance can only be as large as the network allows, thus gaining the maximum score. The slot usage fitness function does not allow for a maximum value to be obtained, causing an apparent



(a) A comparison of the slots used for the two fitness functions



(b) Slot usage fitness versus path distance fitness

Figure 4: Comparison of fitness functions

maximum of approximately 0.8, on which the Pareto frontier lies. Along the top of the plot, the solutions have maximised the path distance score but slot fitness increases as the solution is further to the right. This means every solution on the path-dist = 1.0 line that has a solution to its right is completely dominated by this solution. This means that along this line, the only solution that should be selected is the farthest to the right. With this solution and the others on the plotted line make up the pareto frontier. The two most promising solutions are `slot43` and `dist67`.

8.3. Simulations

The graphs in Figure 5 plots metrics from the output of the TOSSIM simulations, with each column being an output from the GA.

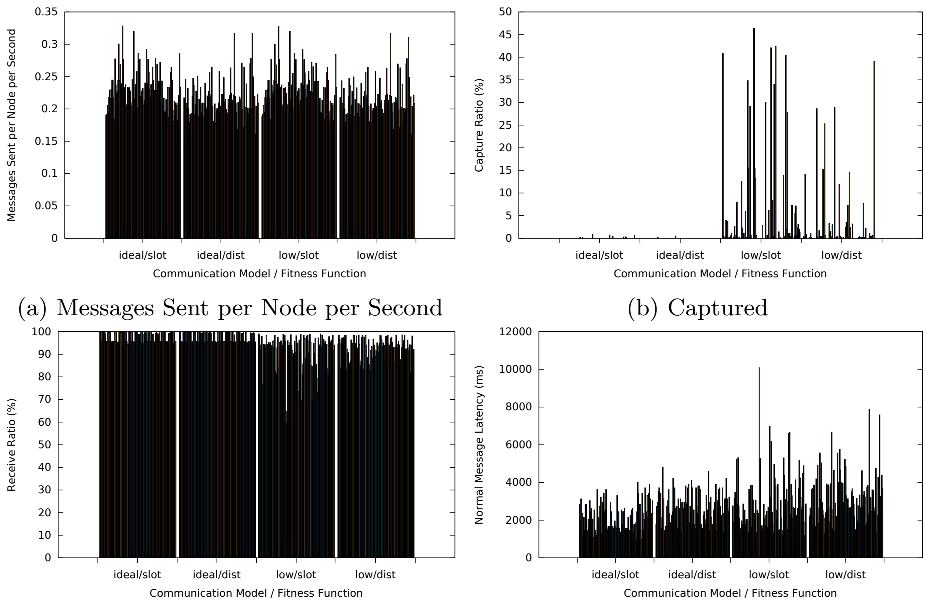
Firstly, Figure 5a shows a plot of messages sent per node per second. Using the rate of message sending rather than total messages sent is a better metric as simulations may not last the full safety period if the attacker happens to capture the source. The rate messages are sent appears similar across fitness functions and identical when changing communication model. This indicates that the differences are caused by slot utilisation, as predicted.

Figure 5b plots the capture ratio of solutions. The plot shows that using the ideal communication model, capture ratio is very low. With low-asymmetry, the capture ratio dramatically increases for both fitness functions, however the additional path distance constraint provides an improvement in both the number of high capture ratio solutions and the level of capture ratio on these solutions. Low-asymmetry causes these issues as the attacker leaves the path that the GA predicts it will follow, due to failing links as well as additional links that the GA did not expect (diagonal communication). This follows the predicted outcome.

Figure 5c plots the message receive ratio of messages sent from the source that are received by the sink. The ideal communication model performs with almost 100% receive ratio while low-asymmetry has a slightly lower rate due to the probability of link failures.

Finally, Figure 5d plots the latency of normal messages sent by the source to be received at the sink. The predicted outcome for all solutions is that the latency is bounded by a single TDMA period, excluding dissemination period. However, a handful of solutions of the low-asymmetry communication model do not abide by this prediction, appearing to approximately double the length of time taken for the message to travel from the source to the sink. A potential reason for this is that the normal messages are generated by the application layer, starting the latency timing, at a point after the transmission slot has ended before the start of the next period. This could lead to a near doubled latency for the message.

The two solutions making up the Pareto frontier are compared in Figure 6, using the low-asymmetry communication model. Messages sent and normal message latency differ between the two solutions due to the total number of slots



(a) Messages Sent per Node per Second (b) Captured

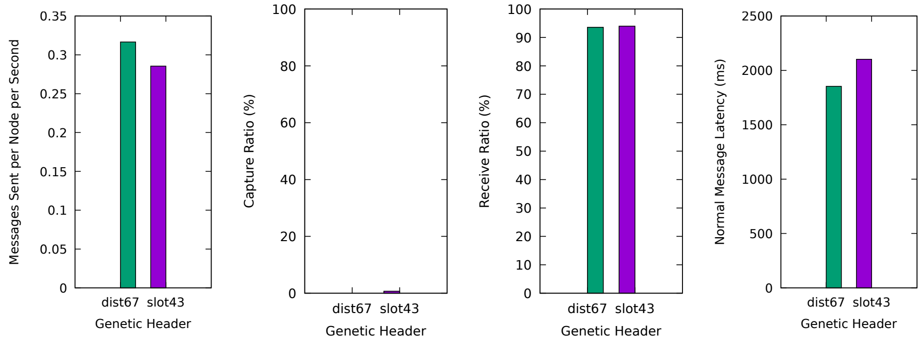
(c) Receive Ratio (d) Latency

Figure 5: Simulation results for 100 outputs from the GA for different GA fitness functions and communication models

used in the network. `dist67` is better in this regard, using less slots results in messages traversing from the source to the sink faster than the `slot43` solution. The receive ratio is very consistent between the two solutions meaning either is a good choice. Finally, capture ratio, while still very small values for both solutions, shows a slight improvement of `dist67` over `slot43`. With these metrics, we can say that the optimal solution for this configuration of all generated solutions is `dist67` as solutions not creating the Pareto frontier where eliminated followed by a metric analysis of those that remained.

8.4. Comparison with NSGA-II

In addition to utilising the Pyevolve framework, early tests were performed using an implementation of NSGA-II [33]. NSGA-II is a multi-objective genetic algorithm that is capable of producing a Pareto frontier by analysing solution



(a) Messages Sent (b) Captured (c) Receive Ratio (d) Latency

Figure 6: Simulation results for the two solutions that lie on the Pareto frontier

domination over one another. The group of solutions that dominate all others but not each other is the Pareto frontier.

Unfortunately, as Figure 7 shows, the Pareto frontier is comprised of a large number of copies of exactly the same solution. It is unclear as to exactly what causes this lack of diversity in the population, however the selection method is the likely culprit, as the other genetic operators function well with the other GA. NSGA-II uses random tournament selection and compares rank followed by crowding distance to determine the better solution. The use of a crowding distance is supposed to aid in the selection of more diverse solutions but this does not appear to be the case for this specific usage.

Due to this selection issue, it also causes early stagnation of the population. Inevitably, this causes NSGA-II to underperform compared with the implementation of the other GA.

8.5. Comparison with other SLP solutions

To the best of our knowledge, this is the first GA-based TDMA scheduling for SLP in WSNs, making comparisons against other such schedules difficult. However, for the sake of completeness, we compare the best solution from our GA algorithm, with two other state-of-the-art algorithms that provide SLP

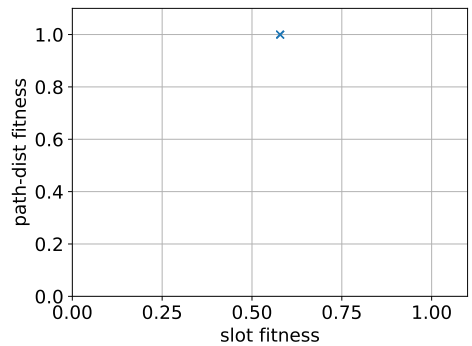


Figure 7: The Pareto frontier output by a single run of NSGA-II

Table 2: The source and safety period combinations for DynamicSPR and ILPRouting in seconds

Source Period	Safety Period
0.125	2.54
0.25	4.57
0.5	8.64
1.0	16.85
2.0	33.76

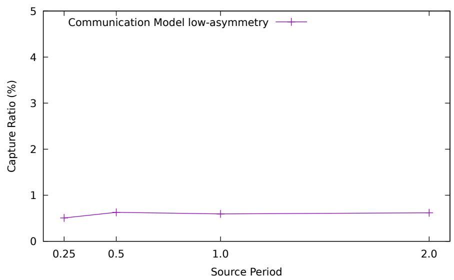
at the routing level, namely *DynamicSPR* [37] and *ILPRouting* [11]. Those two protocols are instances of two classes of SLP protocols: (i) spatially-aware protocol and (ii) temporal-aware protocol [**?**] respectively. Due to the nature of these different protocols, different metrics will be applicable for comparison. Specifically, for spatially-aware protocols, the overhead metric that is most important will be *message* overhead, whereas *latency* is the most important for temporally-aware protocols.

The same network size (11×11) and configuration (source in the top left and sink in the centre) was used for both algorithms to compare with the results gathered in this paper. Further, the same communication and noise models where used for all experiments. The additional parameters for each algorithm were provided to give the best performance for that algorithm. The parameters used for these algorithms are shown in Table 2.

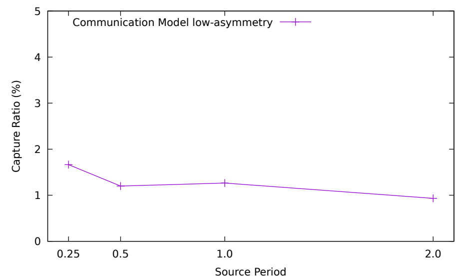
Since DynamicSPR and ILPRouting target the routing level and the GA-based solution targets the MAC level, we address the attacker models used during the comparison: The attacker model for the GA solutions has knowledge of the length of the TDMA period and moves upon hearing the first message during a given period, whereas the other routing protocols use sequence numbers to ensure that attackers are moving in a way as to not follow stale data, again following the first message heard. These different implementations result in very similar behaviour from the attacker models.

Capture ratio: The main metric that will be used for comparison is the capture ratio. Figure 8 shows the capture ratios for the different source periods. The plots show that DynamicSPR has a capture ratio consistently below 1% while that of ILPRouting is slightly higher. Examining Figure 5 again, we can see that under an ideal communication model, the GA solutions perform better than the routing algorithms. This is so due to one main reason: message collisions do not occur when using TDMA, which is not the case when using routing protocols. However, an issue arises when a low-asymmetry communication model is used: The problem that the GA faces is that it assumes vertical and horizontal links are the only links between nodes. When using low-asymmetry, this is not the case as diagonal links can form and links can be broken, which means the attacker can leave, i.e., will not follow, the GA predicted path, potentially capturing the source. This is one issue of a static slot assignment, which can cause more dynamic algorithms to perform better under variable network conditions. Developing an adaptive TDMA algorithm is part of our future work.

However, neither routing algorithm is better than the best produced by the GA, `dist67`, which has a 0% capture ratio (shown in Figure 5b). Combined with the fact that this capture is indefinitely prevented, unlike for the others (which is bounded by a concept called *safety period*), the GA solution is better

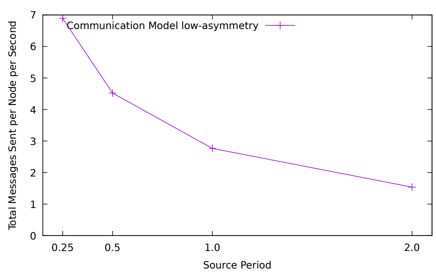


(a) DynamicSPR

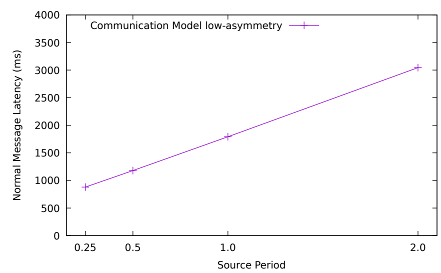


(b) ILPRouting

Figure 8: Capture ratios of different algorithms



(a) DynamicSPR messages sent



(b) ILPRouting latency

Figure 9: Various metrics from DynamicSPR and ILPRouting

than the routing protocols.

Num of messages sent: From Figure 9a, it can be observed that the number of messages sent by the GA-based technique is much less than DynamicSPR. Since DynamicSPR requires fake messages to be sent to be efficient, the number of messages will increase. On the other hand, the only messages that are sent in our GA-based schedule are application messaeges.

Latency: From Figure 9b, it can be observed that the latency induced by the GA-based technique is less than that induced by ILPRouting. The only delay induced for the GA-based technique is the slot assignment, which may be sub-optimal. On the other hand, ILPRouting requires messages to be buffered and aggregated together before being sent. This makes the delay in delivering a message very high.

8.6. Overview of Results

Firstly, we showed some output from the GA that showed the differences between the two fitness functions. This clearly displayed the effectiveness of the optimisation process as the distance fitness function created a path that lead the attacker into the opposite area of the network. We performed simulations on 100 solutions for each fitness function using ideal and more realistic (low-asymmetry) communication models. This showed that for an ideal scenario, the solutions performed with an almost 0% capture ratio for every solution. Using the more realistic model, we can see the effect of additional links and link failures in the network as both fitness functions have increased capture ratio. However, the distance fitness function outperformed the other on average.

We then examined the two solutions that lie on the Pareto frontier in further detail. This allowed us to select the best solution from the 200 solutions (named `dist67`).

We compared the GA generation process to that of a high-performance true multi-objective GA known as NSGA-II but found that it caused early stagnation in the population of solutions, providing inferior results.

Finally, we compared our method with two state-of-the-art algorithms, DynamicSPR [37] and ILPRouting [11]. We show comparable capture ratios under the ideal communication model, with the low-asymmetry communication model being higher. However, the best solution selected outperformed both algorithms in terms of capture ratio.

9. Conclusion

In this paper, the objective was to produce a genetic algorithm solution to generate SLP-aware TDMA schedules. We made a number of contributions: We have mapped the SLP problem to a GA problem that solves for a certain class of attacker (i.e., distributed eavesdropper), producing suitable crossover, mutation and selection operators in the process. We use the concept of Pareto optimality to compare resulting SLP-aware schedules. The optimization criteria were SLP, schedule latency and attacker path. We thus provided two fitness functions, one that reduces total slot usage and one that couples reduced slot usage with directing the predicted attacker path away from the source. We then performed simulations in TOSSIM under ideal and unreliable communication models to show the viability of the optimal schedules, providing a very low capture ratio and a high delivery ratio to the sink. The main advantage of our proposed method is the near optimal capture ratio coupled with path creation that occurs at no additional message overhead.

On the other hand, given that the slot assignment is static, it means that it cannot adapt to the dynamism of the network such as asymmetric links or link failures. This in turn causes attackers to move away from the main predicted path the attacker should have followed, increasing the capture ratio. As such, our current and future work is focused on developing fault-tolerant SLP-aware TDMA schedules.

Acknowledgement

This work was supported by the UK Engineering and Physical Sciences Research Council (EPSRC) [grant number EP/L016400/1].

[1] P. Kamat, Y. Zhang, W. Trappe, C. Ozturk, Enhancing source-location privacy in sensor network routing, in: 25th IEEE International Conference on Distributed Computing Systems (ICDCS'05), 2005, pp. 599–608. doi:10.1109/ICDCS.2005.31.

[2] C. Ozturk, Y. Zhang, W. Trappe, Source-location privacy in energy-constrained sensor network routing, in: Proceedings of the 2nd ACM

workshop on Security of ad hoc and sensor networks, SASN '04, ACM, New York, NY, USA, 2004, pp. 88–93. doi:10.1145/1029102.1029117.

[3] A. Mainwaring, D. Culler, J. Polastre, R. Szewczyk, J. Anderson, Wireless sensor networks for habitat monitoring, in: Proceedings of the 1st ACM International Workshop on Wireless Sensor Networks and Applications, WSNA '02, ACM, New York, NY, USA, 2002, pp. 88–97. doi:10.1145/570738.570751.

[4] A.-M. Badescu, L. Cotofana, A wireless sensor network to monitor and protect tigers in the wild, Ecological Indicators 57 (2015) 447–451. doi:10.1016/j.ecolind.2015.05.022.

[5] J. Kirton, M. Bradbury, A. Jhumka, Source location privacy-aware data aggregation scheduling for wireless sensor networks, in: 2017 IEEE 37th International Conference on Distributed Computing Systems (ICDCS), 2017, pp. 2200–2205. doi:10.1109/ICDCS.2017.171.

[6] R. Srivathsan, S. Siddharth, R. Muthuregunathan, R. Gunasekaran, V. R. Uthariaraj, Enhanced genetic algorithm for solving broadcast scheduling problem in tdma based wireless networks, in: 2010 Second International Conference on COMmunication Systems and NETworks (COMSNETS 2010), 2010, pp. 1–10. doi:10.1109/COMSNETS.2010.5431986.

[7] M. Conti, J. Willemsen, B. Crispo, Providing source location privacy in wireless sensor networks: A survey, IEEE Communications Surveys and Tutorials 15 (3) (2013) 1238–1280. doi:10.1109/SURV.2013.011413.00118.

[8] Y. Xi, L. Schwiebert, W. Shi, Preserving source location privacy in monitoring-based wireless sensor networks, in: 20th International Parallel and Distributed Processing Symposium, 2006, pp. 1–8. doi:10.1109/IPDPS.2006.1639682.

[9] W. Wei-Ping, C. Liang, W. Jian-xin, A source-location privacy protocol in WSN based on locational angle, in: IEEE International Conference on Communications (ICC), 2008, pp. 1630–1634. doi:10.1109/ICC.2008.315.

[10] C. Gu, M. Bradbury, A. Jhumka, Phantom walkabouts in wireless sensor networks, in: Proceedings of the Symposium on Applied Computing, SAC'17, ACM, New York, NY, USA, 2017, pp. 609–616. doi:10.1145/3019612.3019732.

[11] M. Bradbury, A. Jhumka, A near-optimal source location privacy scheme for wireless sensor networks, in: 16th IEEE International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom), 2017, pp. 409–416. doi:10.1109/Trustcom/BigDataSE/ICESS.2017.265.

[12] C. Gu, M. Bradbury, A. Jhumka, M. Leeke, Assessing the performance of phantom routing on source location privacy in wireless sensor networks, in: 2015 IEEE 21st Pacific Rim International Symposium on Dependable Computing (PRDC), 2015, pp. 99–108. doi:10.1109/PRDC.2015.9.

[13] R. Shi, M. Goswami, J. Gao, X. Gu, Is random walk truly memoryless — traffic analysis and source location privacy under random walks, in: INFOCOM, 2013 Proceedings IEEE, 2013, pp. 3021–3029. doi:10.1109/INFCOM.2013.6567114.

[14] A. Jhumka, M. Leeke, S. Shrestha, On the use of fake sources for source location privacy: Trade-offs between energy and privacy, The Computer Journal 54 (6) (2011) 860–874. doi:10.1093/comjnl/bxr010.

[15] A. Jhumka, M. Bradbury, M. Leeke, Fake source-based source location privacy in wireless sensor networks, Concurrency and Computation: Practice and Experience 27 (12) (2015) 2999–3020. doi:10.1002/cpe.3242.

[16] M. Bradbury, M. Leeke, A. Jhumka, A dynamic fake source algorithm for source location privacy in wireless sensor networks, in: 14$^{\text{th}}$ IEEE International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom), 2015, pp. 531–538. doi:10.1109/Trustcom.2015.416.

[17] J. Long, M. Dong, K. Ota, A. Liu, Achieving source location privacy and network lifetime maximization through tree-based diversionary routing in wireless sensor networks, IEEE Access 2 (2014) 633–651. doi:10.1109/ACCESS.2014.2332817.

[18] M. Dong, K. Ota, A. Liu, Preserving source-location privacy through redundant fog loop for wireless sensor networks, in: 13$^{\text{th}}$ IEEE International Conference on Dependable, Autonomic and Secure Computing (DASC), Liverpool, UK, 2015, pp. 1835–1842. doi:10.1109/CIT/IUCC/DASC/PICOM.2015.274.

[19] W. Tan, K. Xu, D. Wang, An anti-tracking source-location privacy protection protocol in WSNs based on path extension, Internet of Things Journal, IEEE 1 (5) (2014) 461–471. doi:10.1109/JIOT.2014.2346813.

[20] Z. Benenson, P. M. Cholewinski, F. C. Freiling, Wireless Sensors Networks Security, IOS Press, 2008, Ch. Vulnerabilities and Attacks in Wireless Sensor Networks, pp. 22–43.

[21] X. Niu, Y. Yao, C. Wei, Y. Liu, J. Liu, X. Chen, A novel source-location anonymity protocol in surveillance systems, in: 2015 International Conference on Identification, Information, and Knowledge in the Internet of Things (IIKI), 2015, pp. 100–104. doi:10.1109/IIKI.2015.30.

[22] K. Mehta, D. Liu, M. Wright, Protecting location privacy in sensor networks

against a global eavesdropper, IEEE Trans. on Mobile Computing 11 (2) (2012) 320–336. doi:10.1109/TMC.2011.32.

[23] Y. Yang, M. Shao, S. Zhu, G. Cao, Towards statistically strong source anonymity for sensor networks, ACM Trans. Sen. Netw. 9 (3) (2013) 34:1–34:23. doi:10.1145/2480730.2480737.

[24] M. Shao, W. Hu, S. Zhu, G. Cao, S. Krishnamurth, T. La Porta, Cross-layer enhanced source location privacy in sensor networks, in: 6^{th} Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON '09), 2009, pp. 1–9. doi:10.1109/SAHCN.2009.5168923.

[25] H. Miao, X. Xiao, B. Qi, K. Wang, Improvement and application of leach protocol based on genetic algorithm for wsn, in: Computer Aided Modelling and Design of Communication Links and Networks (CAMAD), 2015 IEEE 20th International Workshop on, 2015, pp. 242–245. doi:10.1109/CAMAD.2015.7390517.

[26] H. Darji, H. B. Shah, Genetic algorithm for energy harvesting-wireless sensor networks, in: 2016 IEEE International Conference on Recent Trends in Electronics, Information Communication Technology (RTEICT), 2016, pp. 1398–1402. doi:10.1109/RTEICT.2016.7808061.

[27] O. Zorlu, O. K. Sahingoz, Increasing the coverage of homogeneous wireless sensor network by genetic algorithm based deployment, in: 2016 Sixth International Conference on Digital Information and Communication Technology and its Applications (DICTAP), 2016, pp. 109–114. doi:10.1109/DICTAP.2016.7544010.

[28] P. Nagarathna, R. Manjula, Genetic algorithm with a new fitness function to enhance wsn lifetime, in: 2015 International Conference on Applied and

Theoretical Computing and Communication Technology (iCATccT), 2015, pp. 95–100. doi:10.1109/ICATCCT.2015.7456862.

[29] S. M. Duan, J. L. Mao, F. H. Xiang, H. P. Liu, Quantum genetic algorithm optimization in tdma time slot allocation for wsn, in: Control Conference (CCC), 2013 32nd Chinese, 2013, pp. 7377–7382.

[30] G. Chakraborty, Y. Hirano, Genetic algorithm for broadcast scheduling in packet radio networks, in: 1998 IEEE International Conference on Evolutionary Computation Proceedings. IEEE World Congress on Computational Intelligence (Cat. No.98TH8360), 1998, pp. 183–188. doi:10.1109/ICEC.1998.699498.

[31] B. H. Arabi, Solving np-complete problems using genetic algorithms, in: 2016 UKSim-AMSS 18th International Conference on Computer Modelling and Simulation (UKSim), 2016, pp. 43–48. doi:10.1109/UKSim.2016.65.

[32] G. Chiandussi, M. Codegone, S. Ferrero, F. Varesio, Comparison of multi-objective optimization methodologies for engineering applications, Computers & Mathematics with Applications 63 (5) (2012) 912 – 942. doi:https://doi.org/10.1016/j.camwa.2011.11.057.
URL http://www.sciencedirect.com/science/article/pii/S0898122111010406

[33] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A fast and elitist multiobjective genetic algorithm: Nsga-ii, IEEE Transactions on Evolutionary Computation 6 (2) (2002) 182–197. doi:10.1109/4235.996017.

[34] K. D. Lee, T. S. P. Yum, On pareto-efficiency between profit and utility in ofdm resource allocation, IEEE Transactions on Communications 58 (11) (2010) 3277–3285. doi:10.1109/TCOMM.2010.091310.0900102.

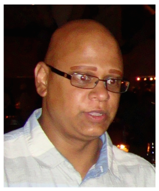
[35] C. S. Perone, Pyevolve: A python open-source framework for genetic algorithms, SIGEVOlution 4 (1) (2009) 12–20. doi:10.1145/1656395.1656397.

[36] A. A. Hagberg, D. A. Schult, P. J. Swart, Exploring network structure, dynamics, and function using NetworkX, in: Proceedings of the 7th Python in Science Conference (SciPy2008), Pasadena, CA USA, 2008, pp. 11–15.

[37] M. Bradbury, A. Jhumka, M. Leeke, Hybrid online protocols for source location privacy in wireless sensor networks, Journal of Parallel and Distributed Computing 115 (2018) 67 – 81. doi:https://doi.org/10.1016/j.jpdc.2018.01.006.
URL http://www.sciencedirect.com/science/article/pii/S0743731518300236

Jack Kirton is a PhD student at the University of Warwick, UK as part of the Warwick Institute for the Science of Cities. He received a BSc in Computer Science followed by an MSc in Data Analytics from Warwick. His current research involves security and fault-tolerance in Wireless Sensor Networks.

Matthew Bradbury is a PhD student at the University of Warwick, UK. He received his MEng degree in Computer Science from Warwick, UK. His current research focus is on security and dependability in Wireless Sensor Networks. He has previously received a best-in-session award at InfoCom 2017.



Arshad Jhumka is an Associate Professor in the Department of Computer Science at the University of Warwick, UK. He received the BA and MA degrees in Computer Science from the University of Cambridge, UK and the PhD degree in Computer Science from the Technical University of Darmstadt, Germany. His research focuses on the design of fault-tolerant and secure systems. His papers have garnered two best paper awards (IEEE DSN 2001 and IEEE HASE 2002) and three of his papers were also best paper award candidates.