

**Optimising control of African sleeping sickness over three  
health zones within the former Bandundu province with a  
shared budget**

by

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# Contents

<b>1</b>	<b>Introduction</b>	<b>1</b>
1.1	What is Human African Trypanosomiasis? . . . . .	1
1.2	Mathematical Modelling . . . . .	3
1.3	Project Outline . . . . .	4
<b>2</b>	<b>Model &amp; Method</b>	<b>6</b>
2.1	Warwick HAT Model . . . . .	6
2.2	Method . . . . .	9
2.3	Calculating Strategy Cost . . . . .	13
2.4	Assumptions . . . . .	15
<b>3</b>	<b>Results</b>	<b>16</b>
3.1	First Glance - Non-Reactive Strategies . . . . .	16
3.2	Budget Distribution - Non-Reactive Strategies . . . . .	19
3.3	First Glance - Reactive Strategies . . . . .	21
3.4	Budget Distribution - Reactive Strategies . . . . .	24
<b>4</b>	<b>Discussion</b>	<b>26</b>
<b>A</b>	<b>Unreactive Optimising DALYs</b>	<b>28</b>
<b>B</b>	<b>Unreactive Optimising PEoT</b>	<b>28</b>
<b>C</b>	<b>Reactive Optimising DALYs</b>	<b>30</b>
<b>D</b>	<b>Reactive Optimising PEoT</b>	<b>34</b>

# 1 Introduction

## 1.1 What is Human African Trypanosomiasis?

Human African trypanosomiasis (HAT) is a vector-borne disease spread by the tsetse fly. There are two forms of the disease caused by *Trypanosoma brucei rhodesiense* and *Trypanosoma brucei gambiense*, respectively. The former, rhodesiense HAT, is endemic in eastern and southern Africa [1]. The latter, gambiense HAT, is endemic in western and central Africa [2].

We will be focusing on gambiense HAT, for which the World Health Organisation (WHO) has set the goal of elimination of transmission by 2030. WHO defines elimination of transmission as a reduction to zero of the incidence of infection with minimal risk of reintroduction, as stated in [3]. From this point, all references to HAT refer to gambiense HAT unless otherwise specified. In support of the achievability of WHO's goal, the global target of less than 2,000 cases a year for HAT by 2020 has already been met. In 2017, for example, fewer than 1,500 cases of HAT were reported [4], the majority of which, 98%, were caused by gambiense HAT [1]. However, HAT has frequently shown its ability to resurge after it appeared to have been brought under control [5].

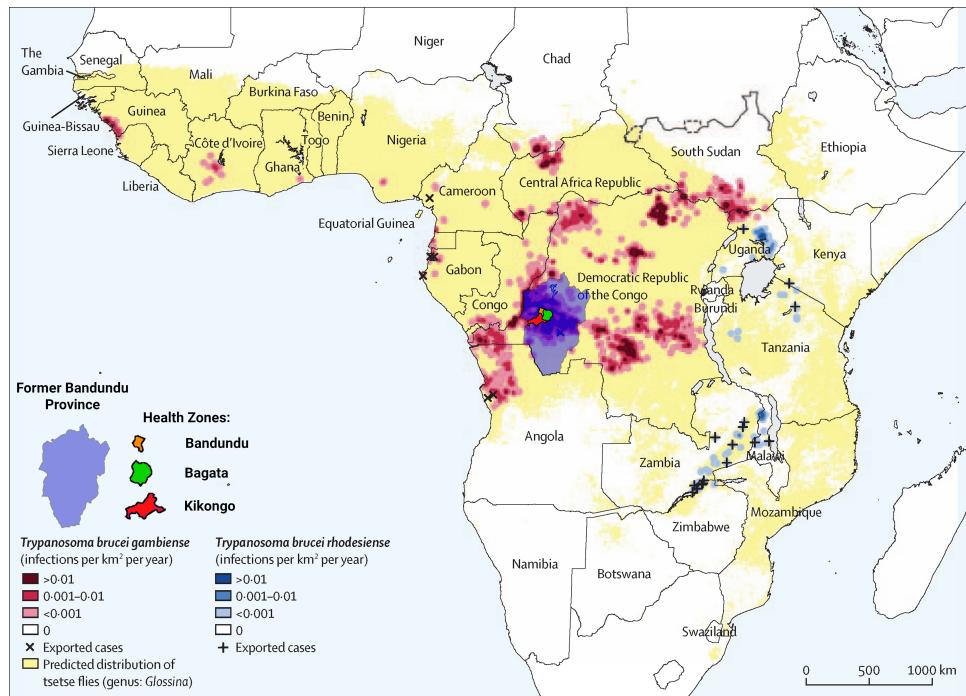


Figure 1: Figure illustrating the geographical distribution of reported infections of HAT (reporting period 2010–14) adapted from [2] under a CC BY to illustrate the health zones we are interested in in the former province of Bandundu

HAT has two stages to infection. During the first stage, an infected individual will experience headaches, fever, enlarged lymph nodes, joints pain, and itching. The second stage

is when the central nervous system is attacked, which leads to disturbance of the sleep cycle among other symptoms. This is what gives the disease its alternative name, African sleeping sickness. HAT is generally considered fatal without treatment [1].

As can be seen in Figure 1, the majority of the world's cases of HAT occur in the Democratic Republic of Congo (DRC), specifically in rural areas due to the large amount of suitable habitat for the tsetse fly. This is why we will focus our project on DRC. We will look at a selection of health zones within DRC, which are subdivisions of the provinces of the country into small populations of around 100,000 individuals [6]. For example, the health zone Bagata within the former Bandundu province had an estimated population of 165,990 in 2015 [7].

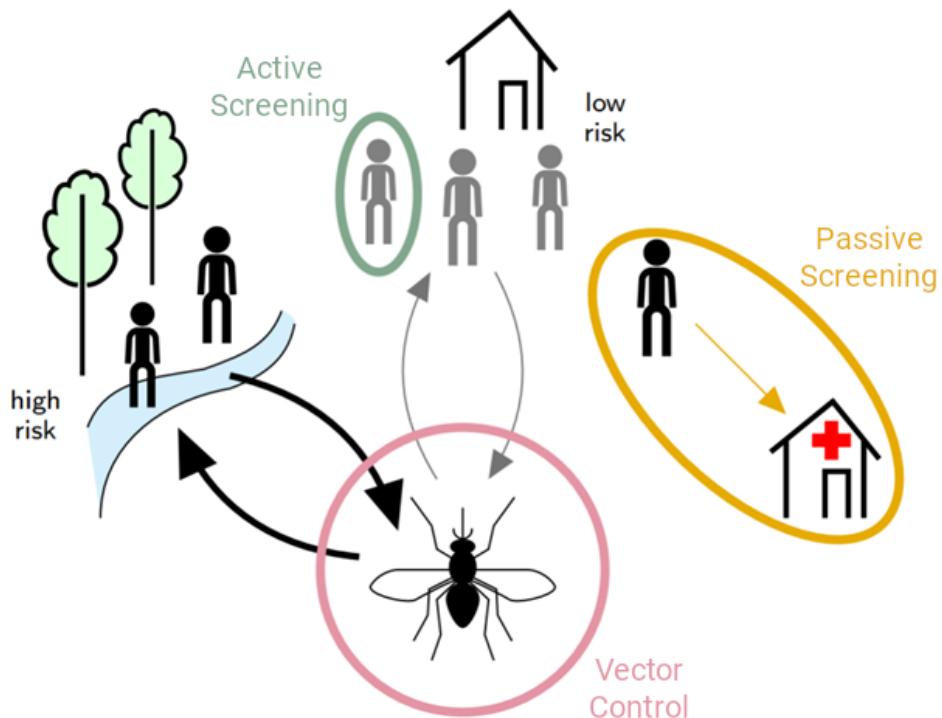


Figure 2: Intervention methods available. This image was taken from [8] under a CC BY license

There are three control methods employed in the goal towards elimination of transmission that we are interested in. Those are passive screening, active screening, and tsetse Tiny Targets as illustrated in Figure 2.

Screening is the testing of individuals for HAT. Passive screening is when an individual goes to a health centre to get tested, while active screening is when testing is done on a given percentage of the population. It is a common assumption in modelling papers that passive screening is ongoing regardless of the number of HAT cases, as individuals will always be able to seek medical assistance when they feel unwell.

Meanwhile, active screening may be turned on and off. The benefit of active screening is that we catch cases sooner, either when the individual is asymptomatic or only has mild symptoms so has not sought medical help yet. This allows for earlier treatment which then reduces the chance of more tsetse flies being infected by this individual. However, active screening requires training of staff, travelling to the individual communities and additional testing all of which increase the cost of intervention.

Tsetse Tiny Targets are small pieces of fabric which the tsetse fly is attracted to. The targets are insecticide coated to kill the tsetse fly. This form of control is known as vector control as it specifically impacts the vector population. Historically vector control has not played a major role in HAT due to the cost of implementing it. However, the introduction of tsetse Tiny Targets offered a more cost-effective form of vector control and modelling has shown the practical role it can play in the elimination of transmission [9]. The use of vector control is further supported by [10].

## 1.2 Mathematical Modelling

Most symptoms related to diseases have been given a disability rating,  $d$ , from 0 to 1. This number represents the severity of symptoms, where 0 is perfect health and 1 equates to death. We can use this number combined with the total time spent infected by individuals, called person-years, to calculate the years lived with disability (YLD). The disability weighting for stages one and two of HAT are 0.14 and 0.54, respectively [8].

By taking the total number of deaths and multiplying by the average number of years longer an individual would have been expected to live, we get the years of life lost (YLL). Disability-adjusted life years (DALYs) is a way to measure the burden a disease has on a population. It is the sum of YLL and YLD, as shown below. A common goal is to find strategies that minimise the total DALYs.

$$\text{DALYs} = \text{YLL} + \text{YLD}$$

These methods can then be used to advise policy makers on the best approach for them to adopt to tackle the transmission of infection. A policy maker will have policy objectives, which are goals they value most. For example, one of WHO's policy objectives for HAT is the elimination of transmission by 2030. The best strategy is dependent on the policy objective that the policy maker is interested in. It is important for a policy maker to rank the priority of policy objectives, as two policies can conflict with each other. For example, minimising DALYs while also minimising the cost of the intervention. To minimise cost you would do nothing, but to minimise DALYs you would likely pick a more expensive approach.

Mathematical modelling has been used to analyse the infection dynamics of HAT in a

variety of different ways. For example, in [11] it was shown that the implementation of vector control can be used to largely improve the chance of elimination of transmission by 2030. By contrast, in [7] mathematical modelling was used to see the impact that coronavirus restrictions could have on the ability to control HAT. The study found that, in the most extreme case they considered, elimination of transmission could be delayed by an average of 2-3 years.

### 1.3 Project Outline

Previously, the modellers in the Zeeman Institute at the University of Warwick have examined four different intervention strategies in five different health zones to ascertain if they helped to achieve elimination of transmission by 2030 [8]. Building upon this, we are interested in finding the best intervention strategy when there is a fixed budget to cover costs up to and including the years 2030 and 2040 that cannot be exceeded. We will be considering the fixed budget over multiple health zones and attempt to find the best strategy-health zone pairing that is within budget. To start with, we will be considering the three health zones Kilkongo, Bandundu, and Bagata in the former Bandundu province, which are shown in Figure 1 and Figure 3.

The two policy objectives we will consider separately are to minimise DALYs and to maximise the probability of elimination of transmission by 2030 (PEoT). We will show that when we wish to minimise DALYs, under a low budget we will prioritise funding of intervention strategies in Bagata and, if we wish to maximise PEoT, under a low budget we will prioritise vector control and interventions in Kikongo first. What we will find is that to maximise PEoT the level of percentage screening will not matter.

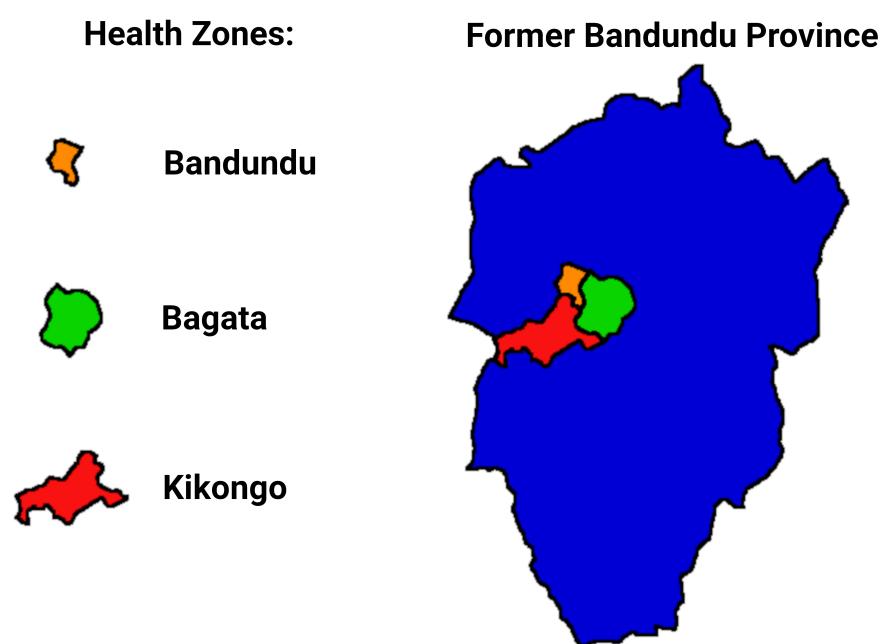


Figure 3: Figure illustrating the geographical locations of the health zones we are interested in in the former Bandundu province.

## 2 Model & Method

### 2.1 Warwick HAT Model

We will be using the Warwick HAT model and code for the optimisation of the spending of funds available to minimise DALYs and to maximise PEoT across all three health zones. The model's underlying transmissions and transitions between classes is deterministic and based on a collection of ordinary differential equations (ODEs), which we can see the dynamics of in Figure 4, for which posterior distributions for the parameters were generated with a Monte Carlo Markov Chains algorithm in [6]. In this model each event, such as an infection from being bitten, has a rate at which it occurs. To account for observational uncertainty in case detection, as well as other events, the outputted number of cases detected is based on a betabinomial distribution that takes the result from the ODE realisation as an input.

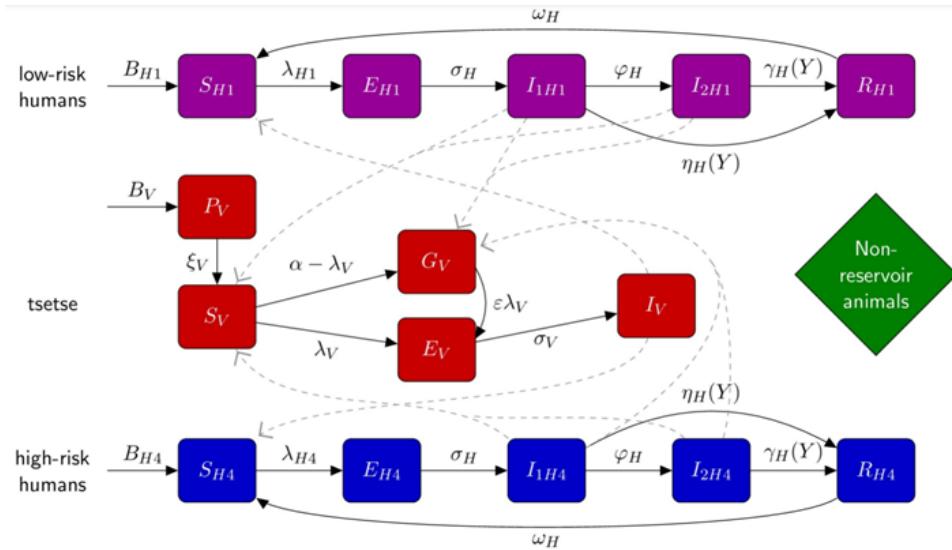


Figure 4: Warwick HAT Model. This Figure is taken from [6] under a CC BY licence.

The Warwick HAT model has 10 classes for humans, split into 5 classes each for high- and low-risk individuals. As explained in [6], low-risk individuals can randomly participate in screening while high-risk individuals never participate in screening. This represents the issue discussed in [11] whereby the working population have already left the village for the day by the time the mobile testing unit arrives. A human can be Susceptible ( $S_{H1}, S_{H4}$ ), Exposed ( $E_{H1}, E_{H4}$ ), Infectious Stage 1 ( $I_{1H1}, I_{1H4}$ ), Infectious Stage 2 ( $I_{2H1}, I_{2H4}$ ), or Recovered ( $R_{H1}, R_{H4}$ ). Exposed individuals have been infected but cannot yet transmit HAT, while the infectious classes represent the two stages of the illness.

The tsetse has 5 classes to distinguish between its early life as a pupae ( $P_V$ ) and its mature life, where we further distinguish between susceptible ( $S_V, G_V$ ), exposed ( $E_V$ ) and infectious ( $I_V$ ) tsetse. Pupae is the development stage of the tsetse and is considered for

more accurate modelling of its life cycle. There are two forms of susceptible tsetse in this model; the first,  $S_V$ , is a tsetse that has yet to have its first blood meal and the second,  $G_V$ , is a tsetse that had its first blood meal from an uninfected individual. The distinction is made because if the first blood meal is not infected the tsetse is less likely to become infected from subsequent blood meals, which is why we have the reduction factor  $\epsilon$  for the rate at which tsetse transition from  $G_V$  to  $E_V$  compared to  $S_V$  transitioning to  $E_V$ . More details of the model are in [12].

The Warwick HAT model allows for reactive strategies, which is used in [8], whereby if no new cases are found three years in a row then vector control and active screening will stop until a new case is detected. A reactive strategy has the benefit that it can significantly reduce the cost of a strategy as less money is spent on intervention. However, reactive strategies can sometimes stop too early, which impacts PEOt and total DALYs. We will be considering both reactive and non-reactive strategies in this report.

Through observing a single realisation in Bagata using 30% active screening once with vector control and once without, we see the benefit of vector control. Figure 5 displays the total person years spent by individuals in Bagata with HAT; for the purpose of plotting we do not distinguish between stage one and stage two. The Warwick HAT model does not implement the use of vector control until 2020, which can be seen in Figure 5 where the total person years rapidly drops off after 2020 for the strategy with vector control. Similarly, Figure 6 shows the sampled deaths for the same two realisations. The person years and deaths are combined to calculate the total DALYs accrued, see Figure 7. We can see that the total DALYs accrued is bounded above by 2,000 for the vector control strategy. However, the DALYs accrued for the strategy without VC exceeds 3,500 by 2035.

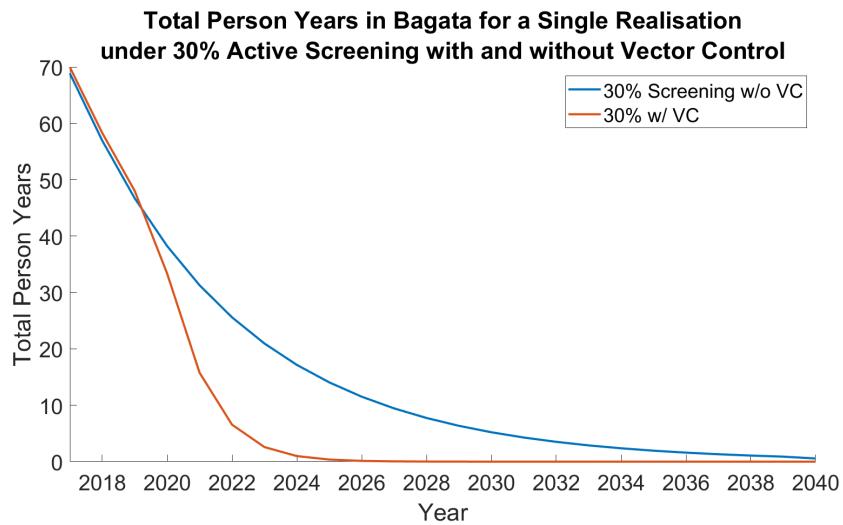


Figure 5: Plot showing the total person years for HAT, without discriminating between stage one and stage two, each year in Bagata from 2017 to 2040 in a single realisation of the Warwick HAT model under the interventions of 30% active screening with and without vector control.

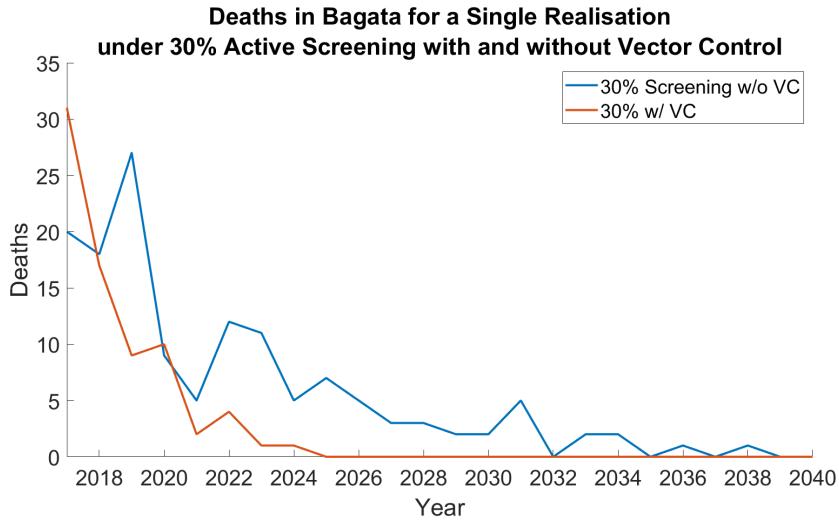


Figure 6: Plot showing the total deaths for HAT, without discriminating between stage one and stage two, each year in Bagata from 2017 to 2040 in a single realisation of the Warwick HAT model under the interventions of 30% active screening with and without vector control.

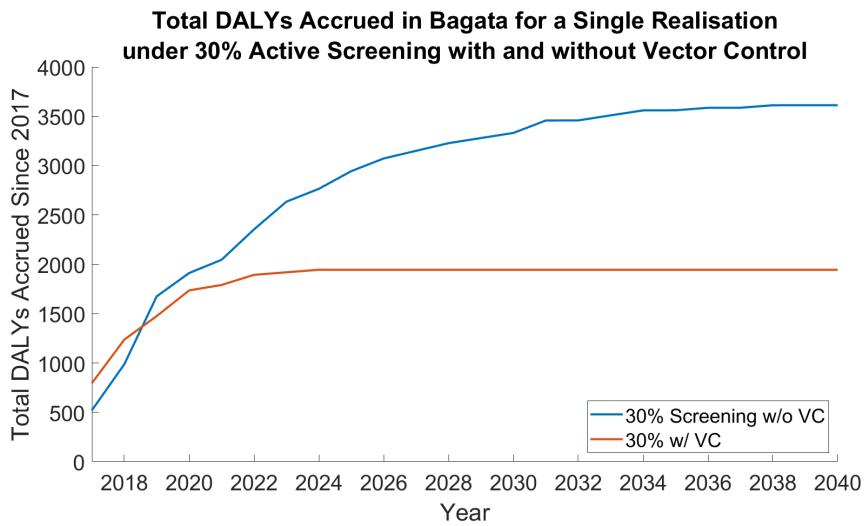


Figure 7: Plot showing the total DALYs accrued for HAT, without discriminating between stage one and stage two, each year in Bagata from 2017 to 2040 in a single realisation of the Warwick HAT model under the interventions of 30% active screening with and without vector control.

## 2.2 Method

For each strategy we will be simulating 10,000 realisations of HAT in each of the health zones Bagata, Bandundu, and Kikongo within the former province of Bandundu. We will say that elimination of transmission has occurred once there are no new infections. By running 10,000 realisations we can approximate the probability of elimination of transmission by 2030.

We will begin by running the model for each health zone under a selection of different strategies. Each strategy will involve the percentage tested during active screening, whether or not vector control is in use, and whether or not the strategy is reactive. We will allow the levels of active screening in the range 0%-150%, were we increase in increments of 5%. It is assumed in the model that, for strategies with more than 80% of the population being screened, there will be two times in the year that testing occurs during which half the percentage of the population given in the strategy will be tested each time. We will record the total deaths, YLD, probability of elimination of transmission by each year, and the cost of strategy in each health zone. We can use the total deaths and the YLD to calculate the DALYs using the equation in section 1.2.

We will then want to pick a strategy for each health zone so that the total cost across all health zones is within budget and best satisfies the policy objective. There are three health zones, each with 31 possible levels of active screening, the choice for vector control, and the choice for reactive screening. In total this gives 1,906,624 possible strategy-health zone pairings and the model has stochastic observations which makes it even more complex. We could brute force this and test all possible strategy-health zone pairings against each other or we can attempt to approximate the optimal solution to reduce the number of simulations required. Taking inspiration from [13], we will determine the best strategy-health zone pairing using a simplified evolution algorithm, Algorithm 1. Our evolution algorithm will work by randomly choosing 60 affordable different strategy-health zone pairings then comparing each pairing against the policy objective.

To reduce the chance of an unaffordable strategy-health zone pairing being picked, we assume that the strategy of doing nothing is the cheapest and consider the cost of each realisation of a strategy in each health zone when paired with doing nothing in the other two health zones for that realisation. If it is unaffordable in more than 5% of the realisations then we remove that strategy from the list of options for that health zone.

We will take the best 20 strategy-health zone pairings and then create 40 new affordable strategy-health zone pairings that will be based on the selected 20 strategy-health zone pairings. For each chosen strategy-health zone pairing, we will create one ‘similar’ strategy-health zone pairing. This similar pairing will replicate the chosen strategy-health zone pairing with a small perturbation in the percentage screened. Then we will create a ‘different’ strategy-health zone pairing by jumping to a different part of the intervention

parameter space. This will be done by switching on/off reactive strategy/vector control or, in the event that this does not create an affordable strategy-health zone pairing, we will generate a new strategy-health zone pairing randomly. In doing so we will be able to maximise the exploration of the parameter space. An example of this over a continuous two-dimensional parameter space can be seen in Figure 8, where level sets of an objective function have been plotted and at each stage the best two points are selected.

This process can be repeated as many times as we wish creating new ‘generations’ of strategy-health zone pairing. The algorithm mimics evolution of a population through survival of the fittest. Algorithm 1 summarises the process. There is no guarantee that the solution found by the algorithm is indeed the optimum one. For this reason, we will run the algorithm ten times and then examine the proposals for the strategy-health zone pairings given. If the same proposal appears twice we will record it once and have one fewer proposal listed.

We will run the algorithm 10 times for 60 generations and for each generation we will test 60 possible strategy-health zone pairings. This gives a total of 32,000 strategy-health zone pairings tested, which is a large reduction from the original pool of a possible 1,906,624 strategy-health zone pairings, thus reducing computational time.

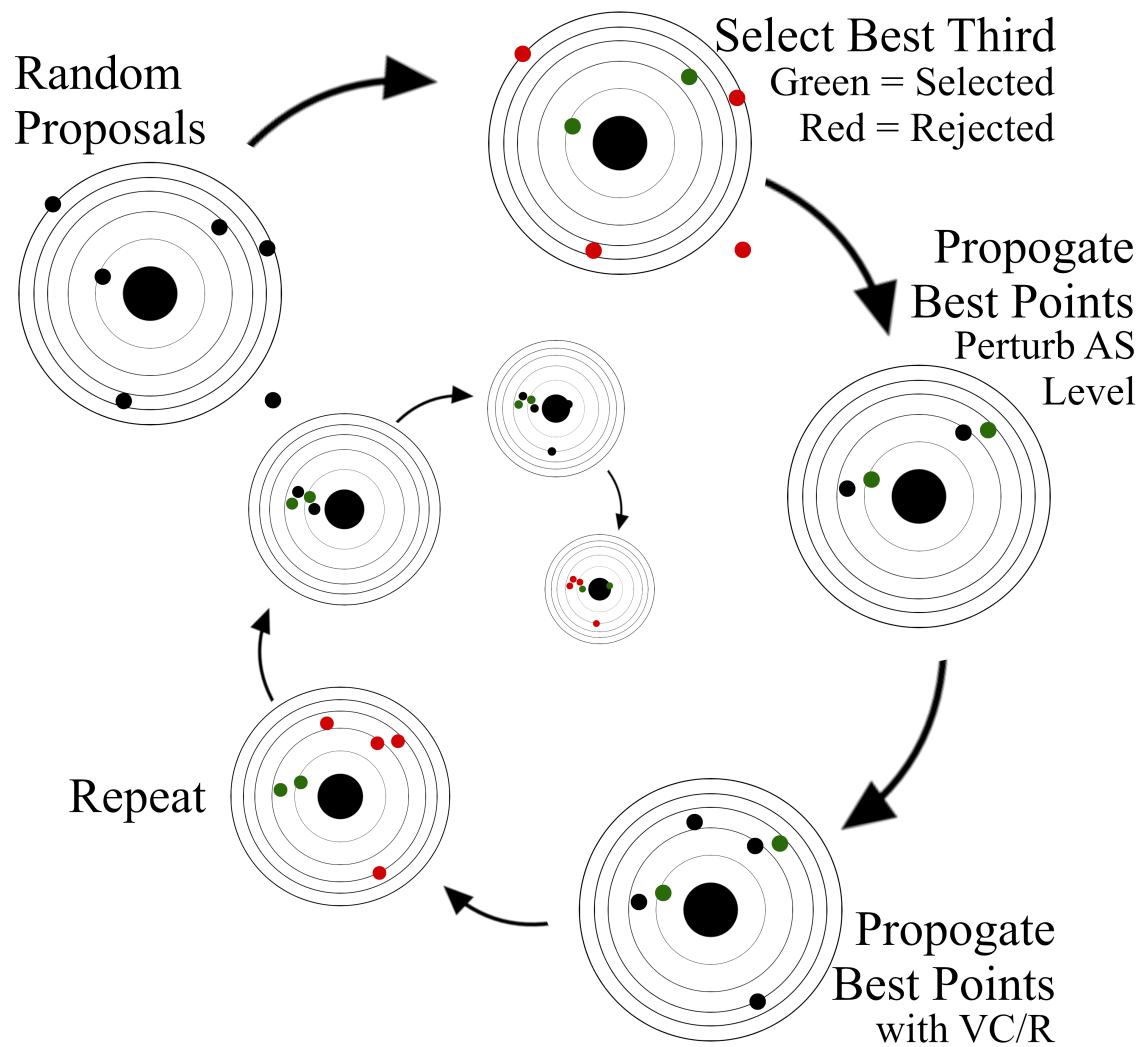


Figure 8: Example of 3 generations of the evolution algorithm over a two-dimensional parameter space with plotted level sets for the cost function. A point is coloured green if it is in the top third of solutions while the rest are coloured red.

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**Algorithm 1:** Evolution Algorithm

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**Result:** Optimum strategy-health zone pairing under a given policy objective

Input: budget, generations,confidence;

```
for i in strategy list do
    for j in health zone list do
        if Strategy i in health zone j combined with doing nothing in other health zones
            exceeds the budget then
            | Discard strategy i from the list of options for health zone j;
        end
    end
end

for i = 1 to 60 do
    affordable = False;
    while !affordable do
        Create strategy-health zone pairing;
        if strategy-health zone pairing within budget then
            | affordable = True;
        end
    end
end

for i = 1 to generations do
    Discard the 40 strategy-health zone pairings that are the worst;
    for Each Remaining strategy-health zone pairing do
        affordable = False;
        while !affordable do
            Create a similar strategy-health zone pairing;
            if strategy-health zone pairing within budget then
                | affordable = True;
            end
        end
        affordable = False;
        while !affordable do
            Create a different strategy-health zone pairing in different part of domain;
            if strategy-health zone pairing within budget then
                | affordable = True;
            end
        end
    end
end

return best strategy-health zone pairing;
```

---

### 2.3 Calculating Strategy Cost

The Warwick HAT model does not output costs, so we will have to calculate this for each realisation and strategy in each health zone. Within a single health zone, the cost of a particular strategy is made up of staff training costs, testing costs, treatment costs, and vector control (VC) costs. We do not consider the cost of the fixed health facilities required for passive screening in the budget calculation, as we assume that it is already covered in the annual health budget.

The cost of active screening in a particular year is considered in [14]. Davis et al. were interested in the difference in cost between the baseline of doing nothing; so all functions are based on the difference in the number of individuals screened compared to the baseline case. We will modify the function slightly to consider the total cost for a given strategy rather than the change in cost and we will also include a cost for the use of VC. This is broken down in Table 1 and the equation below. We assume that for less than 80% active screening there is one visit per year, and for active screening levels equal to or above 80% there are two visits per year [11].

The cost of vector control is dependent on the amount of habitat, such as rivers, in a health zone as tsetse flies live near water. This leads to a variance in the exact yearly cost for tsetse tiny targets from health zone to health zone. We will approximate this cost using the value from the supplementary material from [8]. This gives the yearly cost for vector control in a health zone with 100km of riverbank to cover to be \$55,719. We will use this number for all three health zones; though in reality this number can greatly vary. For example, in the health zone Yasa Bonga the cost was calculated at \$160,954 [8].

$$\text{Total Annual Cost} = \text{VC Cost} + \text{Screening Cost} + \text{Treatment Cost}$$

$$\text{VC Cost} = \mathbb{1}_{\text{VC On}}(\$55,719)$$

$$\begin{aligned} \text{Screening Cost} &= \mathbb{1}_{\text{AS On}}(C_1 N_h + C_2 N_h (\text{No. Active Screening Visits})) \\ &\quad + \mathbb{1}_{\text{AS On}}(C_3 N_h (\% \text{ Screened})) \end{aligned}$$

$$\begin{aligned} \text{Treatment Cost} &= (C_4 + C_5 + C_9)(\text{Stage 1 True Positives}) \\ &\quad + (C_4 + C_5 + C_{10})(\text{Stage 2 True Positives}) \\ &\quad + C_4(\text{Active Screening False Positives}) \end{aligned}$$

Combining the cost for vector control, the cost for screening, and the cost of treatment of confirmed cases gives us the total yearly cost for the given strategy in that health zone. For each strategy in each health zone, the cost will be calculated over multiple realisations and in our evolution algorithm we will use a percentage confidence whereby if the percentage

Table 1: Table Defining Parameters in Equation with values from [14].

Parameter	Meaning	Value
$C_1$	Active screening capital cost per person	\$0.22
$C_2$	Active screening recurrent cost per person	\$0.77
$C_3$	Active screening test cost per person	\$1.03
$C_4$	Confirmation cost per person	\$10.96
$C_5$	Stage determination cost per person	\$1.59
$C_9$	Stage 1 treatment cost per person	\$85.23
$C_{10}$	Stage 2 treatment cost per person	\$561.78

of times a strategy-health zone pairing's total cost is within budget is higher than 95%, we conclude it is affordable. We do not use discounting when calculating the costs, as we wish to consider the total cost when there is a fixed budget available that we cannot exceed. In figure 9, we see the cost of a health-zone strategy pairing over one realisation that would be affordable under an \$8,000,000 budget but not under a \$3,000,000 budget.

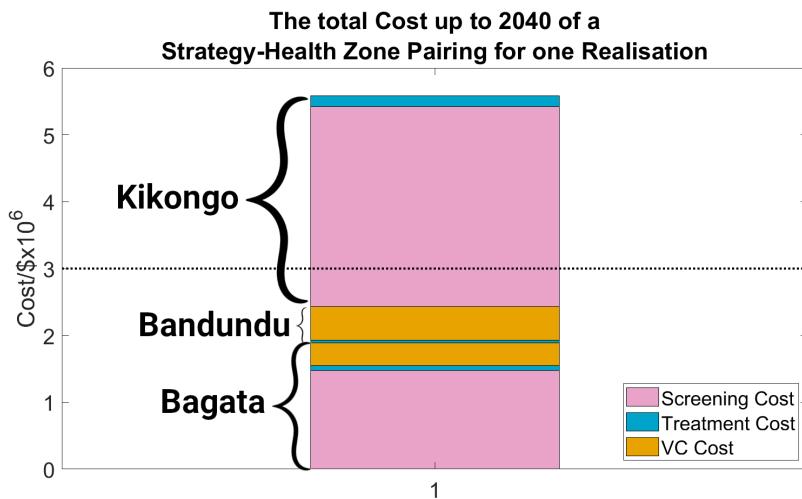


Figure 9: Plot showing total cost up to 2040 of a strategy-health zone pairing for a single realisation. The strategy-health zone pairing involves exclusively reactive strategies with 0%, 15% and 45% active screening in Bandundu, Bagata and Kikongo, respectively as well as vector control in Bagata and Bandundu only.

## 2.4 Assumptions

The Warwick HAT model simulates the dynamics within only one health zone at a time. This assumes that a health zone is a closed system, taking infection spread between health zones to be negligible. We will use this assumption that each health zone is independent, as it will allow us to simulate strategies in each health zone separately. This will reduce the total run time of our simulations as, if we have  $N$  strategies for each health zone, we reduce from  $N^3$  simulations to  $3N$  simulations. This allows us to also assume that the probability of Elimination under a Strategy-Health Zone pairing is the product of the probabilities of elimination in each health zone under its given strategy.

We will also assume that the mapping taking us from percentage screened to our outputs is continuous. This allows us to use the evolution algorithm and justifies the creation of ‘similar’ strategy-health zone pairings. In reality our parameter space is discontinuous due to the switching on/off of vector control and reactive strategies. We assume this is overcome by the creation of new ‘different’ strategy-health zone pairings with each generation to fully explore the parameter space.

## 3 Results

### 3.1 First Glance - Non-Reactive Strategies

The average cost of a non-reactive strategy is shown to increase with the percentage screened in active screening, and switching on vector control causes a further increase as shown in Figures 10 and 11. Two jumps occur in the total cost. The first is increasing active screening from 0% whereby there are now travel and training costs of staff. The second jump occurs at 80% where we assume that there are now two visits to communities to test individuals, so there is an additional travel cost.

For a given strategy, Bagata has the lowest average total cost. By contrast, Kikongo has the highest average total cost. We can understand this when we see that our cost calculation is dependent on the population of the health zone, and by ordering the health zones in terms of average total cost gives us the same order as when they are ranked in order of population size. The cost increases when going from considering the total cost up to 2030, Figure 6, to the total cost up to 2040, Figure 7.

As with calculating the cost, we will not be using discounting when we calculate the total DALYs. The average total DALYs for a non-reactive strategy is shown to decrease with percentage screened and turning on vector control results in a further drop in DALYs, which we see in Figures 12 and 13. The exception is when the level of active screening exceeds 80% and there is a brief increase in DALYs. This lines up with when the screening is split from one session per year into two. By splitting the screening into two sessions we would expect greater levels of DALYs, as the same person can be screened twice which can result in fewer people getting screened that year. Increasing from 0% active screening initially causes a rapid decline in DALYs, but the decline plateaus as we increase percentage screened further. In Figure 14 we see that for all three regions the use of vector control gives a 100% chance of Elimination of Transmission. We also see that increasing the percentage screened in active screening for strategies without vector control increases the PEOt. Bandundu has the highest PEOt without vector control, reaching just under 95% when active screening is at its highest. However, for Bandundu we also see a diminishing return on the PEOt the further we increase active screening. Meanwhile, for Bagata and Kikongo the PEOt remains low for strategies without vector control.

In an ideal world where we did not have to worry about a budget, in order to optimise PEOt we would use vector control in all three regions and we would do the maximum possible screening to simultaneously keep DALYs low.

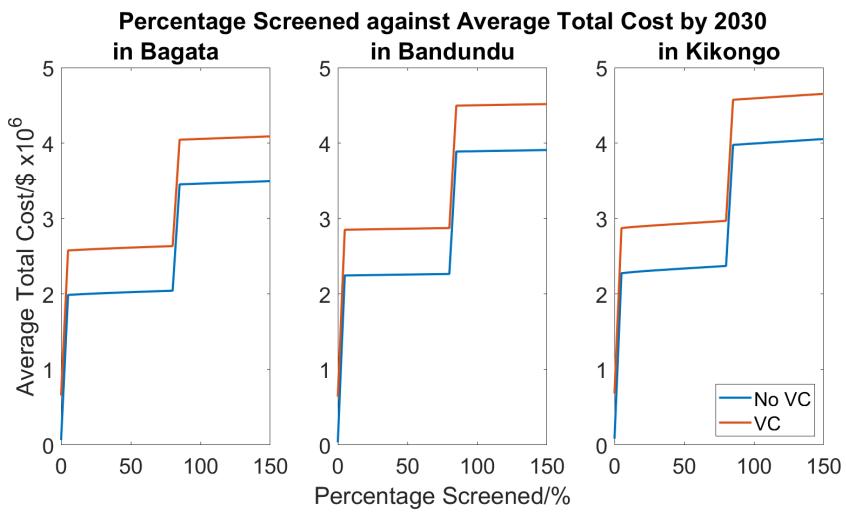


Figure 10: Plot showing average total cost up to 2030 of non-reactive intervention against the percentage of the population screened in active screening.

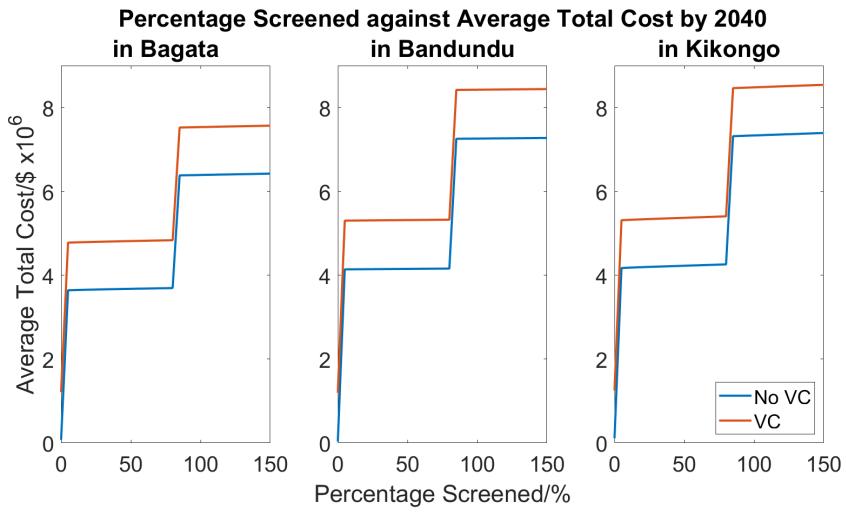


Figure 11: Plot showing average total cost up to 2040 of non-reactive intervention against the percentage of the population screened in active screening.

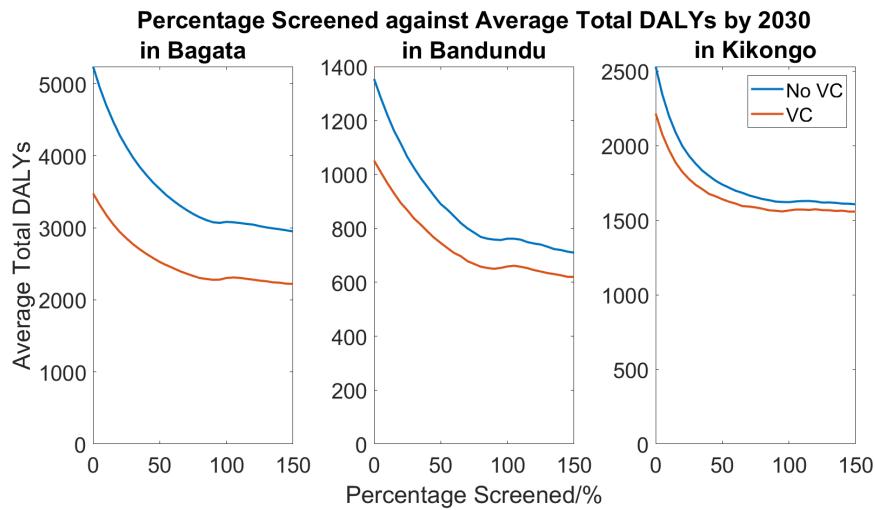


Figure 12: Plot showing average total DALYs up to 2030 for non-reactive interventions against the percentage of the population screened in active screening.

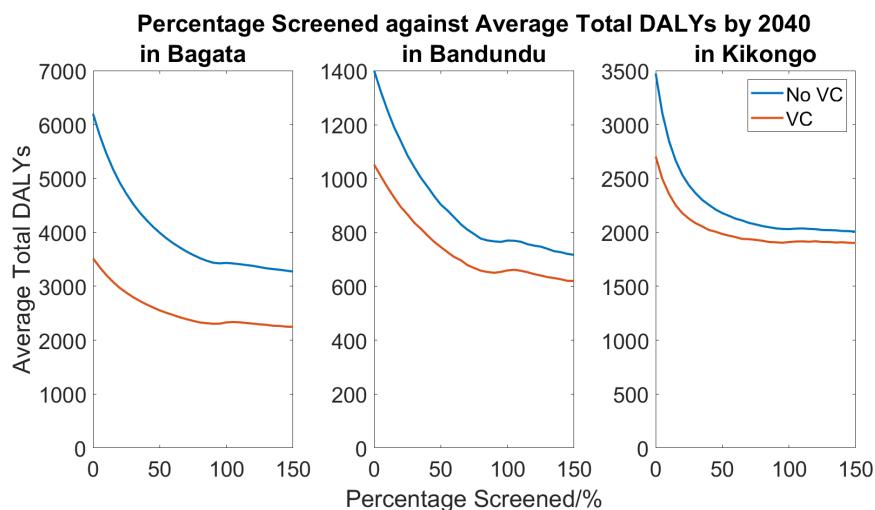


Figure 13: Plot showing average total DALYs up to 2040 for non-reactive interventions against the percentage of the population screened in active screening.

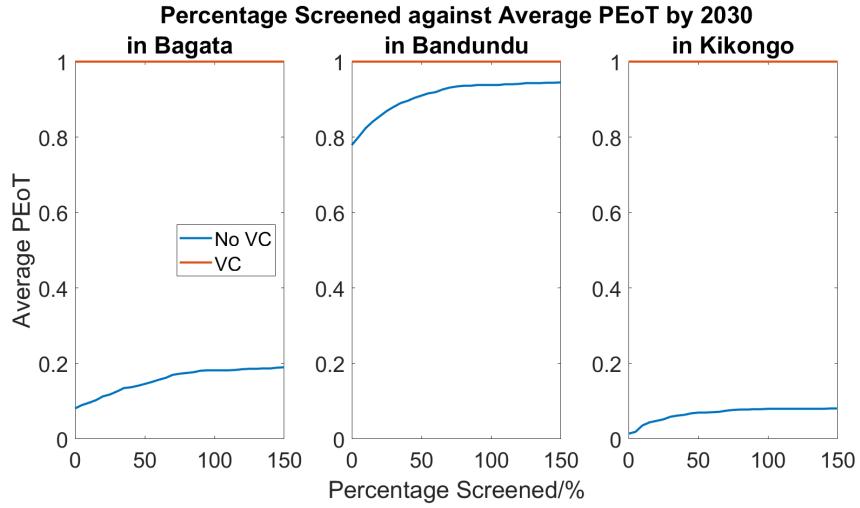


Figure 14: Plot showing average PEOt by 2030 for non-reactive interventions against the percentage of the population screened in active screening.

### 3.2 Budget Distribution - Non-Reactive Strategies

Starting with a limited budget of \$1,000,000 up to 2030, we see the proposal generated by the evolution algorithm in Table 2. This indicates applying vector control to Bagata gives us the best chance of minimising DALYs accrued. By considering the budget up to 2040, the only affordable strategy-health zone pairing is to do nothing.

As we increase the budget, we begin to see the use of 80% active screening in Bagata along with vector control at a budget of \$3,000,000 up to 2030, see Table 2. By contrast, if we consider a budget up to 2040, we have the proposal of no active screening with vector control in Bagata and Kikongo. As we increase the budget further to \$5,000,000 up to 2030, we get the proposal of vector control in all three health zones along with 80% active screening in Bagata. By contrast, if we consider up to 2040 we get the proposal of vector control in all three health zones only to minimise DALYs accrued.

By considering a large budget of \$8,000,000 up to 2030, we have a selection of different proposals from our evolution algorithm, which are listed in order of performance in Table 6 in Appendix A. Figure 20 shows that the best proposal is vector control in Bagata along with 75%, 80%, and 80% active screening in each of Bagata, Bandundu, and Kikongo respectively. This time when we consider the budget up to 2040, we get the proposal being vector control everywhere and 80% active screening in Bagata only.

Now, by contrast, if we consider maximising PEOt we find that at a minimal budget of \$1,000,000 we get the proposal of no active screening and vector control in Kikongo only. As we increase the budget, the algorithm shows a preference for vector control which we can see in Table 3 for which we are proposed vector control everywhere without active screening and if we consider up to 2040 we are proposed vector control in Bagata and

Kikongo only.

When we increase the budget further to \$5,000,000 and \$8,000,000, vector control is now affordable everywhere even up to 2040, so we see proposals of vector control with no preference for the level of active screening.

Table 2: Proposed percentage of active screening to minimise total DALYs where it is highlighted in yellow if vector control is also recommended.

Budget	Consider up to	Bagata	Bandundu	Kikongo
\$1M	2030	0%	0%	0%
\$3M	2030	80%	0%	0%
\$5M	2030	80%	0%	0%
\$8M	2030	75%	80%	80%
\$1M	2040	0%	0%	0%
\$3M	2040	0%	0%	0%
\$5M	2040	0%	0%	0%
\$8M	2040	80%	0%	0%

Table 3: Proposed percentage of active screening to maximise PEOt where it is highlighted in yellow if vector control is also recommended.

Budget	Consider up to	Bagata	Bandundu	Kikongo
\$1M	2030	0%	0%	0%
\$3M	2030	0%	0%	0%
\$5M	2030	0%	70%	0%
\$8M	2030	0%	50%	70%
\$1M	2040	0%	0%	0%
\$3M	2040	0%	0%	0%
\$5M	2040	0%	0%	0%
\$8M	2040	0%	0%	0%

### 3.3 First Glance - Reactive Strategies

The average cost of a reactive strategy follows a similar trend to the cost of non-reactive strategies, which we see in Figures 15 and 16. However, the reactive strategies consistently have a lower cost than their non-reactive counterparts, and this difference grows further when we consider the total cost up to 2040. Furthermore in Bandundu, after an initial increase in average cost when active screening is turned on without vector control, increasing the percentage screened from 5% to 80% shows a decrease in average cost. In Bagata and Bandundu, with the exception of when the active screening percentage is at 150%, the use of vector control actually leads to a decrease in the average total cost. We also see that the jump in costs due to an additional testing visit when the active screening percentage increases beyond 80% is smaller for reactive strategies than non-reactive strategies.

The average total DALYs, as shown in Figures 17 and 18, follows a similar trend to that of their non-reactive counterpart. Increasing from 0% active screening initially causes a rapid decline in DALYs but the decline plateaus as we increase percentage screened further. In figure 19 we see that for all three regions the use of reactive vector control gives a near 100% chance of elimination of transmission by 2030, similar to that of the non-reactive counterpart. We also see that increasing the percentage screened in active screening for strategies without vector control increases the PEOt; this, however, is bounded from above by its non-reactive counterpart. For both DALYs and PEOt, we see that there is no major loss caused by transitioning to a reactive strategy.

In an ideal world where we did not have to worry about a budget, in order to optimise PEOt we would not use a reactive strategy. The performance of a reactive strategy is bounded by its non-reactive counterpart.

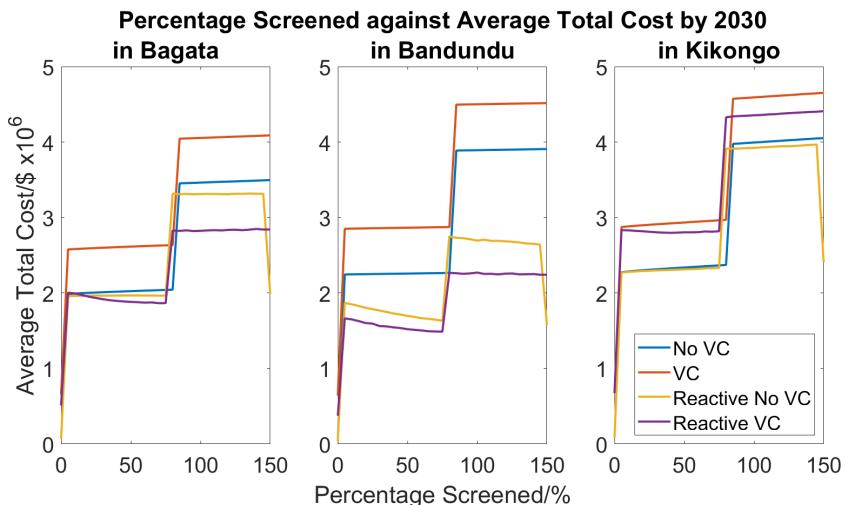


Figure 15: Plot showing average total cost up to 2030 for intervention strategies against the percentage of the population screened in active screening.

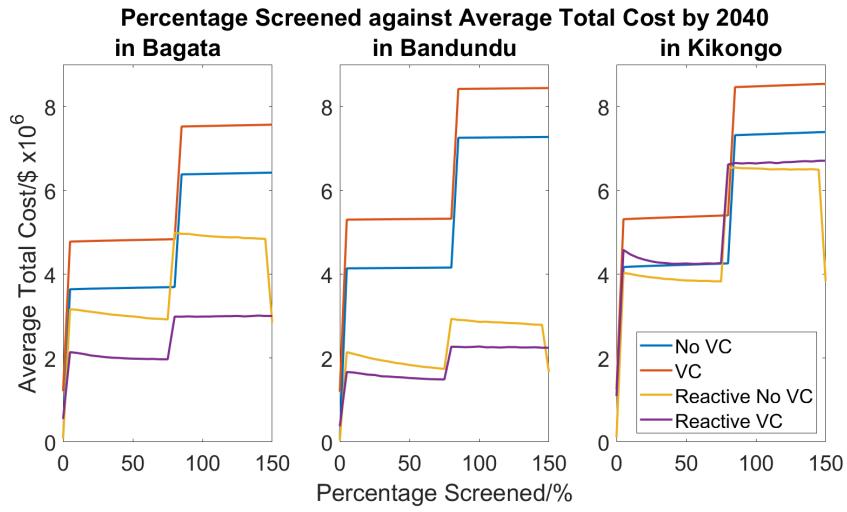


Figure 16: Plot showing average total cost up to 2040 for intervention strategies against the percentage of the population screened in active screening.

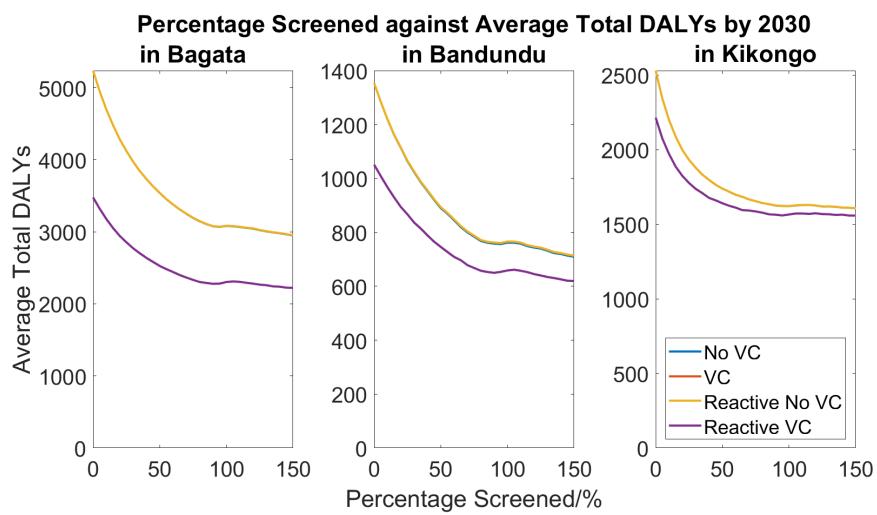


Figure 17: Plot showing average total DALYs up to 2030 for intervention strategies against the percentage of the population screened in active screening.

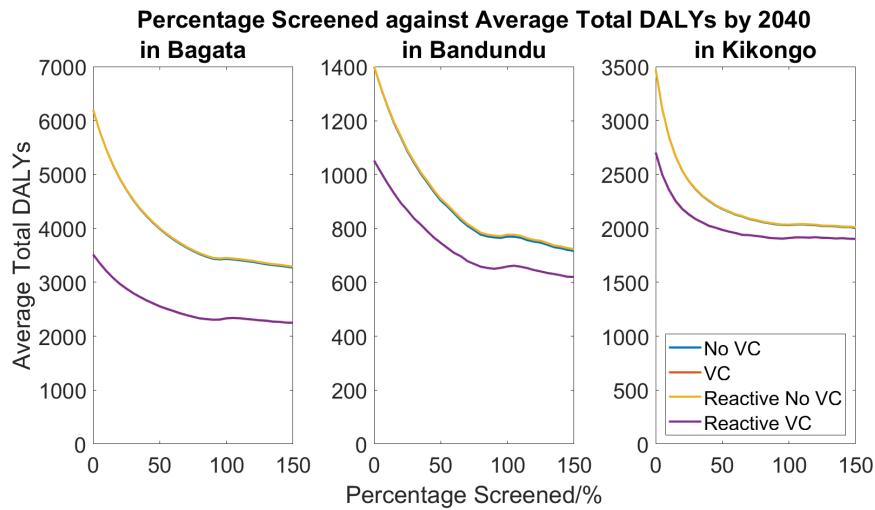


Figure 18: Plot showing average total DALYs up to 2040 for intervention strategies against the percentage of the population screened in active screening.

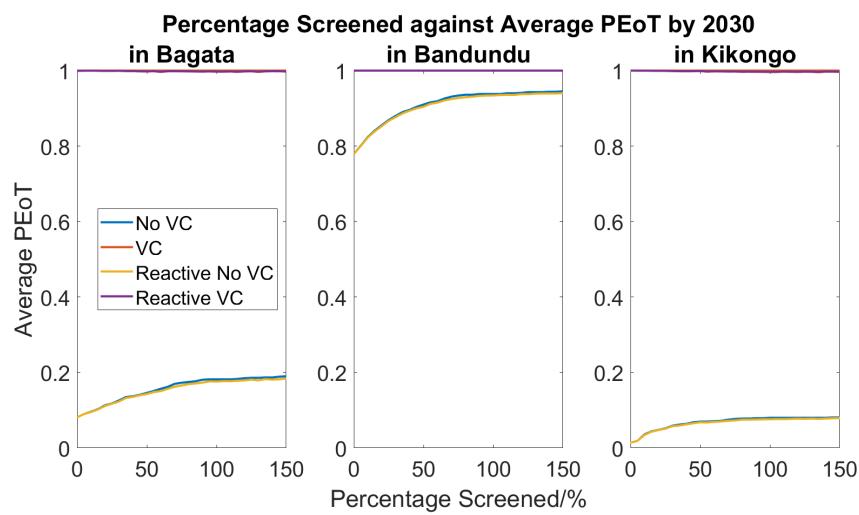


Figure 19: Plot showing average PEOt by 2030 for intervention strategies against the percentage of the population screened in active screening.

### 3.4 Budget Distribution - Reactive Strategies

The introduction of reactive strategies allows for a greater range of affordable options, which raises the question how does this impact the evolution algorithm's recommendation?

At a limited budget of \$1,000,000 and \$3,000,000 up to 2030, when we look at minimising DALYs accrued we see no change in the proposal. However, if we consider up to 2040, for a budget of \$1,000,000 we now have the proposal of reactive vector control in Bandundu. Then, for a budget of \$3,000,000 we have the proposal of vector control everywhere making use of reactive strategies to make the proposal more affordable.

For a budget of \$5,000,000 up to 2030, we now can afford active screening in more than one health zone due to reactive strategies. As we can see in Figure 21, the best proposal is reactive vector control along with 75% and 70% active screening in Bagata and Bandundu respectively. When we consider this budget up to 2040, we find the best strategy-health zone pairing to be vector control everywhere along with 75% active screening in Bagata and reactive strategies in Bagata and Bandundu. The proposals and their performance can be seen in Table 13 and Figure 22.

Finally, at a budget of \$8,000,000 up to 2030, we are able to have higher levels of active screening courtesy of reactive strategies, see Table 14. Figure 23 demonstrates that the best strategy-health zone pairing is vector control everywhere along with 65%, 75%, and 50% active screening in Bagata, Bandundu, and Kikongo, respectively. Considering the budget up to 2040, we get the proposals shown in Table 25. By looking at Figure 25, we can see that the best proposal is vector control in Bagata and Bandundu along with 65% active screening in Bagata and Kikongo.

When we consider a budget to maximise the PPeoT we find that the proposals follow the same trend as the non-reactive proposals. With low budgets we focus on vector control in Kikongo and, as we increase the budget further, we add vector control elsewhere with no preference for the level of active screening.

Table 4: Proposed percentage of active screening to minimise total DALYs where it is highlighted in yellow if vector control is also recommended and it is underlined when the strategy is reactive.

Budget	Consider up to	Bagata	Bandundu	Kikongo
\$1M	2030	0%	0%	0%
\$3M	2030	80%	0%	0%
\$5M	2030	75%	70%	0%
\$8M	2030	65%	75%	50%
\$1M	2040	0%	0%	0%
\$3M	2040	0%	0%	0%
\$5M	2040	75%	0%	0%
\$8M	2040	65%	0%	65%

Table 5: Proposed percentage of active screening to maximise PEoT where it is highlighted in yellow if vector control is also recommended and it is underlined when the strategy is reactive.

Budget	Consider up to	Bagata	Bandundu	Kikongo
\$1M	2030	0%	0%	0%
\$3M	2030	0%	0%	0%
\$5M	2030	0%	0%	45%
\$8M	2030	80%	105%	0%
\$1M	2040	0%	0%	0%
\$3M	2040	0%	0%	0%
\$5M	2040	0%	0%	0%
\$8M	2040	80%	0%	0%

## 4 Discussion

What we have found is that, depending on the policy objective, the proposed strategy-health zone pairing will vary. Considering the policy objective of minimising total DALYs accrued, under a small budget funding is prioritised for Bagata. We can understand this by looking at Figures 15 and 16, where we see that non-reactive strategies cost less to implement in Bagata than Bandundu and Kikongo. Furthermore, when we look at Figures 17 and 18, we see that turning on vector control lowers the DALYs in Bagata substantially more than in Bandundu and Kikongo.

By contrast, for the policy objective of maximising the PEoT, under a small budget funding is prioritised for vector control over active screening and Kikongo is the first to receive vector control. By looking at Figure 19, we see that the use of vector control almost guarantees the elimination of transmission. Furthermore, we see that without vector control, regardless of the level of active screening, the average PEoT is capped at 20% and 10% in Bagata and Kikongo, respectively. Meanwhile, Bandundu exceeds an average PEoT of 95% using just active screening. Through this we can see why Kikongo, Bagata and then Bandundu is the order under which they are recommended vector control as the total budget is increased.

While these are the best strategy-health zone pairings looking only at the data, can these strategies be justified? For example, Table 4, shows that for a \$3,000,000 budget to minimise the total DALYs accrued up to 2030 we should provide 80% active screening and vector control in Bagata and do nothing in Bandundu and Kikongo. While this reduces the DALYs accrued, we are doing nothing to help individuals in Bandundu and Kikongo. A policy maker may feel uneasy providing minimal aid to Bandundu and Kikongo, both of which accrue more DALYs than Bagata.

To reduce the run time of the code and to avoid implementing travel between nearby health-zones, we made the assumption that the disease dynamics were independent of each other in each health zone. To make our results more accurate this is something we could re-consider in future work, but due to the limited movement between health zones we believe this to be a reasonable assumption.

The Warwick HAT Model is deterministic with sampling. Due to this, vector control guarantees PEoT in a health zone. Perhaps if we considered a stochastic model, we might find that the vector control does not guarantee elimination of transmission in a health zone, in which case there may be a preference for the percentage of active screening along with vector control.

While our evolution algorithm showed no preference for the level of percentage active screening, a policy maker may choose to go for the highest level of percentage active screening affordable in each health zone along with vector control. This would lower the

total DALYs accrued along with maximising the PEoT.

We based our cost analysis on the work done by Davis et al., which used older cost estimates. In [15], Snijders et al. perform a cost comparison of the traditional mobile teams and the new mini-mobile teams introduced in 2014. It was found that the cost per person screened for a mini-team is 15% cheaper than the traditional mobile teams. Snijders et al. attribute this reduction in cost to cheaper means of transportation, fewer human resources, and different testing techniques. Using these costs in this project may have impacted the total strategy costs and final strategy-health zone pairing proposals.

We ran 1,000 realisations of the Warwick HAT model for each strategy in each health zone, and for each realisation we took 10 betabinomial samples. This process took approximately 72 hours to run and, had there been more time available, we could have ran for a greater number of realisations to more accurately estimate the PEoT and the DALYs for each strategy-health zone pairing. There is a diminishing return experienced on the gain in accuracy of the PEoT and the DALYs as we increase the number of realisations. Given the time available, we concluded that 1,000 realisations and 10 betabinomial samples per realisations would be sufficient in approximating the PEoT and the DALYs for the purposes of this project.

In our intervention parameter space, we allowed active screening up to and including 150%. We assumed that the percentage of active screening chosen was always achieved. For high levels of percentage active screening, achieving that level of screening may not be possible. As discussed in [11], based on focus group discussions in five health zones of Kasai-Oriental province of DRC, there are a range of reasons individuals may choose not to get screened despite being aware of the severity of HAT. Some reasons given for not attending were the lack of confidentiality during the screening procedure, fear of lumbar punctures, distrust toward the nursing staff, and the mobile testing teams often arrive and leave while the working population are away from the village at work. The latter reason is already accounted for in the Warwick HAT model, whereby only low-risk individuals get tested for HAT in active screening.

In many of our budgets, the proposals involved vector control without any active screening. For example, in Table 18 we see that the best proposal is vector control everywhere with no active screening. While this maximises the PEoT, it is in conflict with WHO recommendations. WHO indicates that vector control should be used as part of an integrated strategy along with screening [16].

## A Unreactive Optimising DALYs

Since we ran the evolution algorithm multiple times we often gained more than one unique proposal for larger budgets. We see in Table 6, the proposals for a budget of \$8,000,000 up to 2030 along with their performance against each other in Figure 20.

Table 6: Proposed strategy-health zone pairings to minimise total DALYs up to 2030 for a total budget of \$8,000,000 up to 2030.

Proposal No.	Bagata	Bandundu	Kikongo	Frequency
1	75%	80%	80%	1
2	45%	45%	30%	2
3	70%	80%	75%	1
4	40%	40%	35%	1
5	75%	70%	80%	1
6	65%	70%	55%	1
7	70%	80%	45%	1
8	70%	70%	65%	1
9	65%	70%	65%	1

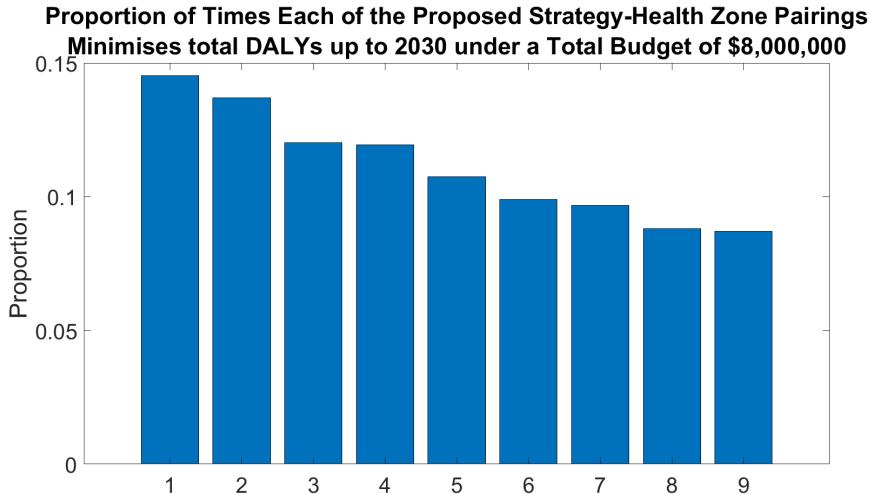


Figure 20: Plot showing proportion of times each of the proposed strategies minimises the total DALYs up to 2030 under a budget of \$8,000,000.

## B Unreactive Optimising PEOt

A collection of additional proposals for maximising PEOt with unreactive strategies. Multiple strategies were proposed for budgets of \$5M and \$8M.

Table 7: Proposed strategy-health zone pairings to maximise PPeT by 2030 for a total budget of \$5,000,000 up to 2030.

Proposal No.	Bagata	Bandundu	Kikongo	Frequency
1	0%	70%	0%	1
2	45%	0%	0%	1
3	0%	0%	35%	1
4	0%	40%	0%	2
5	0%	55%	0%	2
6	0%	0%	45%	1
8	0%	5%	0%	1
9	0%	25%	0%	1

Table 8: Proposed strategy-health zone pairings to maximise PPeT by 2030 for a total budget of \$8,000,000 up to 2030.

Proposal No.	Bagata	Bandundu	Kikongo	Frequency
1	0%	50%	70%	1
2	55%	0%	35%	1
3	0%	75%	85%	1
4	75%	70%	0%	1
5	10%	0%	0%	1
6	125%	15%	0%	1
7	0%	145%	40%	1
8	95%	0%	50%	1
9	5%	60%	0%	1
10	40%	100%	0%	1

Table 9: Proposed strategy-health zone pairings to maximise PPeT by 2030 for a total budget of \$8,000,000 up to 2040.

Proposal No.	Bagata	Bandundu	Kikongo	Frequency
1	0%	0%	0%	1
2	60%	0%	0%	1
3	30%	0%	0%	1
4	0%	0%	75%	2
5	15%	0%	0%	1
6	0%	15%	0%	1
7	0%	0%	65%	1
8	0%	20%	0%	1
9	0%	60%	0%	1

## C Reactive Optimising DALYs

Collection of proposals for minimising total DALYs accrued and considering reactive strategies with budgets of \$3M, \$5M, and \$8M with their respective performances shown in the Figures 21, 22, 23, and 25.

Table 10: Proposed strategy-health zone pairings to minimise total DALYs up to 2030 for a total budget of \$1,000,000 up to 2030.

Proposal No.	Bagata	Bandundu	Kikongo	Frequency
1	0%	0%	0%	3
2	0%	0%	0%	7

Table 11: Proposed strategy-health zone pairings to minimise total DALYs up to 2040 for a total budget of \$3,000,000 up to 2040.

Proposal No.	Bagata	Bandundu	Kikongo	Frequency
1	0%	0%	0%	5
2	0%	0%	0%	4
3	0%	0%	0%	1

Table 12: Proposed strategy-health zone pairings to minimise total DALYs up to 2030 for a total budget of \$5,000,000 up to 2030.

Proposal No.	Bagata	Bandundu	Kikongo	Frequency
1	75%	70%	0%	1
2	70%	75%	0%	1
3	150%	0%	80%	1
4	65%	75%	0%	1
5	80%	65%	0%	1
6	150%	0%	60%	1
7	60%	70%	0%	1
8	80%	0%	0%	1
9	80%	45%	0%	1
10	80%	0%	0%	1

Table 13: Proposed strategy-health zone pairings to minimise total DALYs up to 2040 for a total budget of \$5,000,000 up to 2040.

Proposal No.	Bagata	Bandundu	Kikongo	Frequency
1	75%	0%	0%	7
2	75%	0%	0%	3

Table 14: Proposed strategy-health zone pairings to minimise total DALYs up to 2030 for a total budget of \$8,000,000 up to 2030.

Proposal No.	Bagata	Bandundu	Kikongo	Frequency
1	65%	75%	50%	1
2	70%	60%	60%	1
3	80%	70%	75%	1
4	60%	130%	75%	1
5	45%	130%	70%	1
6	50%	135%	70%	1
7	80%	75%	40%	1
8	80%	70%	70%	1
9	80%	75%	70%	1
10	80%	75%	70%	1

Table 15: Proposed strategy-health zone pairings to minimise total DALYs up to 2040 for a total budget of \$8,000,000 up to 2040.

Proposal No.	Bagata	Bandundu	Kikongo	Frequency
1	65%	0%	65%	1
2	60%	0%	80%	1
3	75%	0%	75%	1
4	75%	0%	70%	1
5	75%	0%	80%	1
6	150%	75%	0%	1
7	145%	75%	0%	1
8	135%	75%	0%	1
9	140%	75%	0%	2

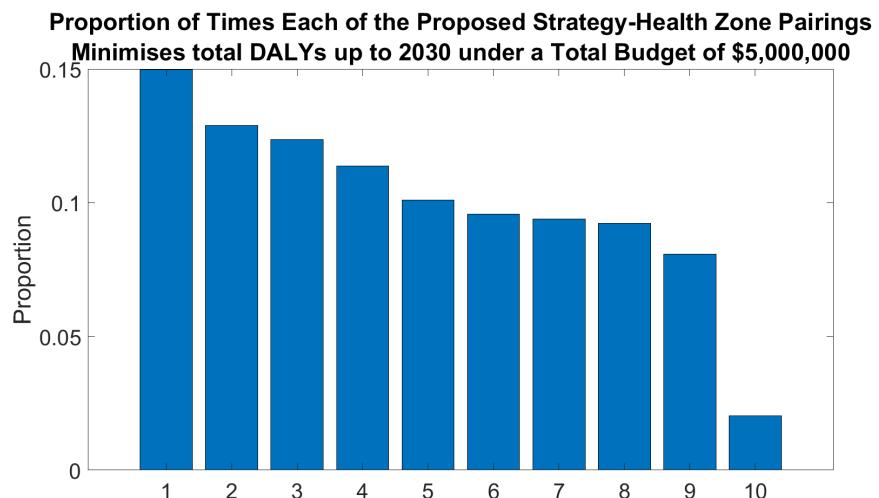


Figure 21: Plot showing proportion of times each of the proposed strategies minimises the total DALYs up to 2030 under a budget of \$5,000,000.

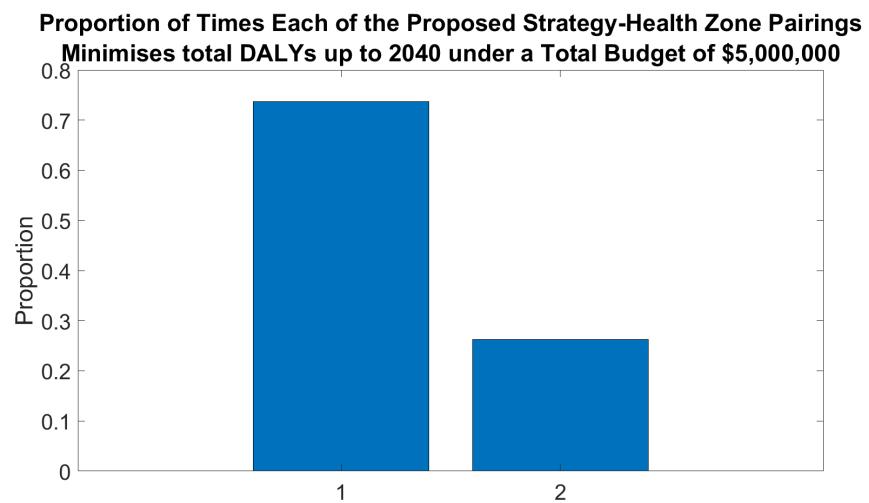


Figure 22: Plot showing proportion of times each of the proposed strategies minimises the total DALYs up to 2040 under a budget of \$5,000,000.

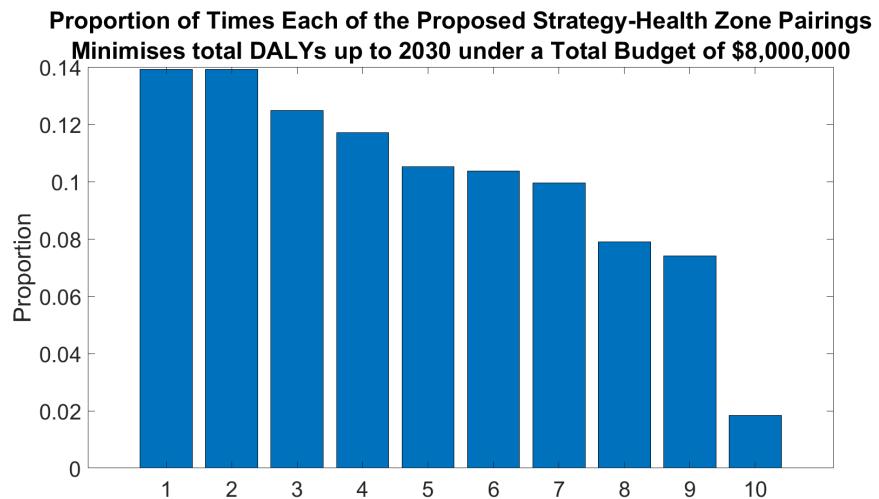


Figure 23: Plot showing proportion of times each of the proposed strategies minimises the total DALYs up to 2030 under a budget of \$8,000,000.

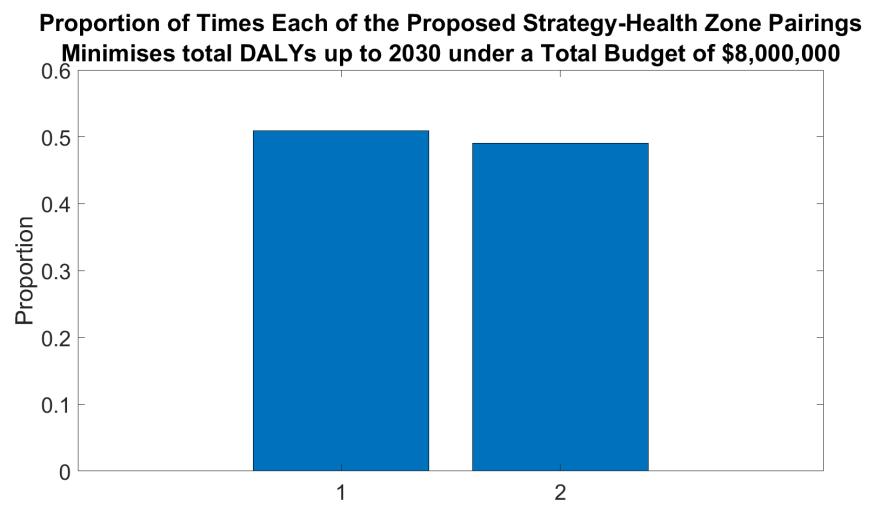


Figure 24: Plot showing proportion of times each of that proposals 1 and 2 minimise the total DALYs up to 2030 with respect to the other under a budget of \$8,000,000.

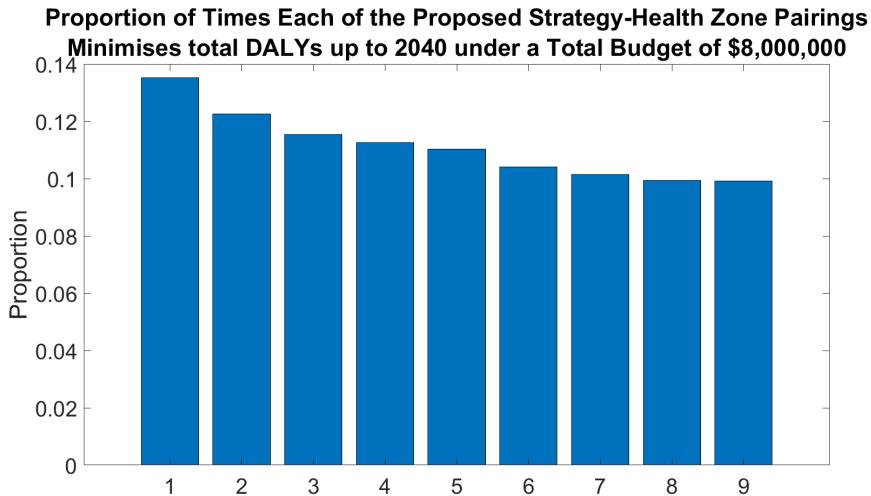


Figure 25: Plot showing proportion of times each of the proposed strategies minimises the total DALYs up to 2040 under a budget of \$8,000,000.

## D Reactive Optimising PEoT

Additional tables, listing proposals generated by the evolution algorithm in order to maximise the PEoT.

Table 16: Proposed strategy-health zone pairings to maximise PEoT by 2030 for a total budget of \$3,000,000 up to 2030.

Proposal No.	Bagata	Bandundu	Kikongo	Frequency
1	0%	0%	0%	8
2	0%	150%	0%	2

Table 17: Proposed strategy-health zone pairings to maximise PPeT by 2030 for a total budget of \$5,000,000 up to 2030.

Proposal No.	Bagata	Bandundu	Kikongo	Frequency
1	0%	0%	45%	1
2	0%	150%	65%	1
3	55%	0%	0%	1
4	0%	0%	30%	1
5	0%	0%	40%	1
6	0%	5%	0%	1
7	60%	150%	0%	1
8	0%	0%	15%	1
9	25%	0%	0%	1
10	0%	0%	25%	1

Table 18: Proposed strategy-health zone pairings to maximise PPeT by 2030 for a total budget of \$5,000,000 up to 2040.

Proposal No.	Bagata	Bandundu	Kikongo	Frequency
1	0%	0%	0%	8
2	0%	150%	0%	2

Table 19: Proposed strategy-health zone pairings to maximise PPeT by 2030 for a total budget of \$8,000,000 up to 2030.

Proposal No.	Bagata	Bandundu	Kikongo	Frequency
1	35%	150%	30%	1
2	60%	0%	100%	1
3	80%	105%	0%	1
4	145%	0%	20%	1
5	10%	20%	0%	1
6	45%	55%	0%	1
7	120%	0%	75%	1
8	0%	55%	45%	1
9	40%	150%	35%	1
10	120%	45%	0%	1

Table 20: Proposed strategy-health zone pairings to maximise PEOt by 2030 for a total budget of \$8,000,000 up to 2040.

Proposal No.	Bagata	Bandundu	Kikongo	Frequency
1	0%	150%	35%	2
2	80%	0%	0%	1
3	0%	0%	10%	1
4	50%	0%	0%	1
5	45%	0%	0%	1
6	0%	5%	0%	1
7	0%	0%	50%	1
8	65%	0%	0%	1
9	20%	0%	0%	1

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