OPTIMIZING FOGGING AREAS IN DENGUE VECTOR CONTROL STRATEGIES USING GENETIC ALGORITHMS

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ABSTRACT

Purpose:This study aims to address the persistent challenge of dengue fever in Malaysia, particularly in the context of rapid urbanization and its impact on the rise of vector-borne diseases. It evaluates the effectiveness of different resource allocation strategies in dengue vector control by applying genetic algorithm-based fitness functions to optimize decision-making. This study contributes to the field of public health logistics by demonstrating how algorithmic optimization can improve the strategic deployment of limited resources in urban vector control operations.

Design/methodology/approach: A comparative analysis of four fitness functions was conducted using a genetic algorithm framework to simulate resource distribution for dengue control. Fitness Function 1 applies uniform allocation, Fitness Function 2 incorporates severity-based weighting, Fitness Function 3 ranks areas by case counts, and Fitness Function 4 integrates both rank and variability. The performance and impact of each approach were assessed based on allocation efficiency and ability to target high-risk zones.

Findings: Results indicate a clear progression in allocation effectiveness from the basic Fitness Function 1 to the more complex Fitness Function 4. While Fitness Functions 2 and 3 show improvements by focusing on severity and case count, respectively, Fitness Function 4 provides the most balanced and strategic allocation. It enhances resource efficiency by accounting for both severity and variability in dengue incidence, leading to improved targeting and reduced disease burden.

Research limitations/implications (if applicable): The study is based on simulated models and secondary data, which may not fully capture real-world complexities such as human behavior, environmental variability, and cross-agency coordination. Future research should incorporate real-time field data and stakeholder feedback to validate model outcomes.

Practical implications (if applicable): The findings support the integration of advanced optimization techniques in public health planning. By adopting Fitness Function 4, health authorities can allocate resources more effectively, prioritize high-risk areas, and enhance the overall impact of dengue control strategies, especially in rapidly urbanizing regions.

Originality/value: This research introduces a novel application of genetic algorithm-based fitness functions for optimizing vector control efforts. By comparing multiple prioritization strategies, it provides valuable insights into data-driven dengue management and highlights the importance of adaptive and targeted intervention planning.

Keywords: Resource allocation, Dengue vector control, Genetic algorithm, Optimization techniques

Introduction

Dengue is a major global public health concern, affecting more than 120 countries worldwide. In 2019 alone, an estimated 5.2 million cases were reported (WHO, 2022). Although dengue threatens approximately 50% of the global population, Asia accounts for 70% of the disease burden (WHO, 2022). To address this, the World Health Organization (WHO) launched the Global Strategy for Dengue Prevention and Control (2021–2030), which aims to reduce the case fatality rate of dengue to zero by 2030 (WHO, 2020). In Malaysia, the first recorded case of dengue fever (DF) occurred in December 1901 in Pulau Pinang (MOH, 2017). Large-scale outbreaks emerged in 1973, with 969 reported cases and 54 deaths (7.3 per 100,000 population) (Cheah et al., 2016; Vythilingam and Wan-Yusoff, 2017). Since then, dengue has been classified as endemic, occurring throughout the year. In response, the Vector Control Program was established in 1974 under Malaysia's National Dengue Prevention and Control Program (MOH, 2022). The programme focuses on identifying the sources and causes of dengue infections at specific locations. Reported cases are entered into the system and monitored by the Communicable Disease Control (CDC) unit at district health offices. Environmental health officers investigate the cases to determine infection sources, after which rapid response teams are deployed within 24 hours. These teams implement control measures within a 200- to 400-metre radius of the reported case. Control strategies primarily target Aedes aegypti and Aedes albopictus, the two main mosquito vectors responsible for transmitting the dengue virus (Ong, 2016).

Despite progress in surveillance and control, Malaysia continues to face challenges in managing dengue effectively. Rapid urbanisation has been a major driver of increased vector-borne diseases in urban areas (Basar et al., 2018). Researchers have suggested that urban growth will likely contribute to the emergence of new vector-borne diseases, particularly those transmitted by Aedes mosquitoes. These mosquitoes are highly adaptable to climate change, human activities, and global trade, which has accelerated the spread of the dengue virus (Bouzid et al., 2018; Majid et al., 2020). Furthermore, dense populations and continuous construction in urban centres create ideal breeding habitats for Aedes mosquitoes, complicating the timely implementation of vector control strategies (Majid et al., 2016). Overall, Malaysia's efforts to reduce dengue spread have had some success, but there are significant drawbacks that limit their efficacy. Vector control programs in Malaysia face challenges due to limited financial resources for implementation, supervision, and evaluation. To overcome these limitations, the government must implement comprehensive and consistent measures involving sustained efforts, multi-floated strategies, and strong collaboration between relevant agencies. By doing so, effective dengue vector control can be achieved, reducing the burden of dengue fever on the population.

Mathematical optimisation and optimal control theory have been widely applied in vector-borne disease management, providing structured approaches to determine how and when to deploy limited intervention resources. These models typically define control actions such as spraying intensity, larval source reduction, or public education as variables within a cost-minimisation framework. Studies demonstrate that such models can generate non-intuitive yet effective intervention schedules, such as pulsed spraying or targeted efforts at critical times, which outperform uniform strategies (Libotte et al., 2020; Chamnan et al., 2021). This highlights the role of algorithmic optimisation in supporting evidence-based decision-making for dengue control operations.

Budgetary and logistical constraints are another critical dimension in dengue control, making constrained optimisation models highly relevant. Approaches based on linear and integer programming, knapsack formulations, and multi-objective optimisation help decision-makers answer questions such as how to allocate a fixed budget across intervention types, or which neighbourhoods to prioritise under manpower constraints. Evidence suggests that targeted, optimisation-guided allocations are more cost-effective than uniform spending, with marked improvements in cases averted per unit cost (Sirisena & Noordeen, 2014; Rodríguez-Barraquer et al., 2015; Caminade et al., 2019). This is particularly important in urban public health logistics, where funds and field staff are limited. Recent advances also extend optimisation frameworks to novel interventions, such as Wolbachia-infected mosquito releases, and explore hybrid pipelines that combine forecasting, optimisation, and surveillance feedback loops. However, challenges remain in operationalising these tools, especially due to uncertainties in case reporting and the need for community engagement (Stoddard et al., 2013; Achee et al., 2015; Harish et al., 2024). In this study, a mathematical optimization approach using genetic algorithms is applied in order to maximize fogging areas as one of dengue control strategies.

Methodology

Data description

Number of dengue cases registered from 2011 to 2023 for State of Kedah, Malaysia were collected, with the severity level of each district differs. There are 11 districts in Kedah which are Baling (BL), Bandar Baharu (BB), Kota Setar (KS), Kuala Muda (KM), Kubang Pasu (KP), Kulim (KL), Langkawi (LG), Padang Terap (PT), Pendang (PG), Sik (SK) and Yan(YN). The severity level is determined by DMOSS classification as shown in Table 1. By taking dengue cases from 2011 to 2023, only KM is categorized as district with high burden of dengue cases, followed by BL, KS, KP and KL as districts with a moderate burden of dengue cases (Refer Table 2). The rest of districts were categorized as low burden (BB, LG, PT, PG, SK and YN).

Table 1: DMOSS locality Stratification

Categories	**Description**
High burden (B1)	More than equal to 7 cases per week
Moderate burden (B2)	More than equal to 1.7 cases per week
Low burden (B3)	Less than 1.7 cases per week

Table 2: DMOSS locality Stratification by Districts

District	***BL***	***BB***	***KS***	***KM***	***KP***	***KL***	***LG***	***PT***	***PG***	***SK***	***YN***
Severity	B2	B3	B2	B1	B2	B2	B3	B3	B3	B3	B3

Model Formulation

The mathematical model for the study is written in the form of a linear function, with the objective function to maximize the coverage area (in km²) of fogging activities in each area within each district.

Let X_i represent the coverage in km^2 of fogging activity in District i, where i ranges from 1 to 11 representing the districts listed. Objective function to maximize the coverage of fogging activities is written as:

$$Maximize\ Z = \sum_{i=1}^{11} x_{ij}$$

Subject to the following constraints:

1 Total manpower at each district, $\boldsymbol{A_i}$:

$$\boldsymbol{A_1 \leq 22,\ A_2 \leq\ 14,\ A_3 \leq\ 24,\ A_4 \leq\ 34,\ A_5 \leq 18,\ A_6 \leq\ 26,\ A_7 \leq\ 12,\ A_8 \leq\ 18,\ A_9 \leq\ 14,\ A_{10} \leq\ 16,\ A_{11} \leq\ 8}$$

2 Total manpower constraint:

$$A_1 + A_2 + \cdots + A_{11} \leq 206$$

3 District-specific insecticide constraints:

$$S_{ik}\ \leq Stock\ of\ insecticide\ type\ k\ in\ District\ i$$

$\boldsymbol{k}$ =**1 (Gokilahts)**	$\boldsymbol{k}$ = **2 (Malathion TG)**	$\boldsymbol{k}$ = **3 (Actellic 50EC)**
$\boldsymbol{S_{11}} \leq$ **278.56**	$S_{12} \leq 106.76$	$S_{13} \leq 16.64$

$\boldsymbol{S_{21}} \leq$ **67.52**	$S_{22} \leq 14.40$	$S_{23} \leq 10.00$
$\boldsymbol{S_{31}} \leq$ **835.00**	$S_{32} \leq 220.00$	$S_{33} \leq 60.00$
$\boldsymbol{S_{41}} \leq$ **939.00**	$S_{42} \leq 191.00$	$S_{43} \leq 36.00$
$\boldsymbol{S_{51}} \leq$ **415.00**	$S_{52} \leq 90.00$	$S_{53} \leq 22.00$
$\boldsymbol{S_{61}} \leq$ **574.75**	$S_{62} \leq 225.40$	$S_{63} \leq 7.50$
$\boldsymbol{S_{71}} \leq$ **289.30**	$S_{72} \leq 24.00$	$S_{73} \leq 3.84$
$\boldsymbol{S_{81}} \leq$ **51.34**	$S_{82} \leq 0.00$	$S_{83} \leq 0.00$
$\boldsymbol{S_{91}} \leq$ **128.96**	$S_{92} \leq 55.84$	$S_{93} \leq 10.00$
$\boldsymbol{S_{101}} \leq$ **80.21**	$S_{102} \leq 0.00$	$S_{103} \leq 0.00$
$\boldsymbol{S_{111}} \leq$ **57.36**	$S_{112} \leq 7.20$	$S_{113} \leq 0.00$

Where:

$$\sum_{i=1}^{11} S_{i1} \leq 3717.00 \text{ litres}$$
$$\sum_{i=1}^{11} S_{i2} \leq 934.60 \text{ litres}$$
$$\sum_{i=1}^{11} S_{i3} \leq 165.98 \text{ litres}$$

4 Total stock of insecticides constraint:

$$S_1 + S_2 + \cdots + S_{11} \leq 4817.58\ litres$$

5 Budget constraints, C_i:

$$C_1 \leq 104{,}931.44$$
$$C_2 \leq 52{,}465.72$$
$$C_3 \leq 157{,}397.17$$
$$C_4 \leq 157{,}397.17$$
$$C_5 \leq 52{,}465.72$$
$$C_6 \leq 157{,}397.17$$
$$C_7 \leq 52{,}465.72$$
$$C_8 \leq 52{,}465.72$$
$$C_9 \leq 52{,}465.72$$
$$C_{10} \leq 52{,}465.72$$
$$C_{11} \leq 52{,}465.72$$

Parameters Settings

In order to achieve the maximum coverage area, different strategies are considered. In this study, the strategy on how areas for resource allocation are prioritised (Qiu et al., 2022). Four approaches are considered. Fitness Function 1 offers a uniform approach, treating all regions equally. Fitness function 2 introduces severity-based weighting, improving efficiency by focusing on high-severity areas. Fitness function 3 shifts to a rank-based method, prioritizing areas with more cases, while fitness function 4 goes a step further by accounting for variability, making it the most refined and strategic approach. These differences significantly affect the model's performance and results. Fitness function 1, being the simplest, may converge quickly but at the expense of effectiveness, as it fails to prioritize high-risk areas. Fitness functions 2 and 3 offer more targeted solutions, but fitness function 4 delivers the most balanced resource allocation, adjusting for both case severity and variability. The lines of code where these differences are introduced are pivotal to how the genetic algorithm operates, with each fitness function evolving in complexity and refinement.

The model is run and solved based on four approaches in allocating the fogging areas. Table 3 summarises the description of each allocation approach. Note that each trial is run on three initial population sizes of 10, 50, and 100, with a maximum iteration of 2000. The number of runs was also set at 2000.

Table 3: Summary of Allocation Approaches for Dengue Resource Deployment

Trial	Allocation Approach	Description
1	Base Model (Normal)	Define the coverage function "LOW" = 1, "MODERATE" = 2, "HIGH" = 3

2	Base Model (Severity-based)	Define severity weights "Low" = 1, "Moderate" = 2, "High" = 3
3	GA based Rank Weighted Mean (single criterion)	Rank the mukims based on dengue cases count, weights them and normalize between 0 to 1
4	GA based Rank Weighted Mean (single criterion) using std dev & variance	i) Compute variance and standard deviation for the criterion. ii) Adjust weights: assign lower weights to criteria with higher variability. iii) Implement RVM: use the adjusted weights in the fitness function.

Analysis and Findings

The original resource allocation across the 11 districts serves as the baseline for comparison. This allocation, which distributes manpower, insecticide, and budget without optimization, offers a reference point for understanding the effectiveness of the genetic algorithm (GA) outputs. For instance, KS was allocated 35 personnel, 835 litres of Insecticide 1, 220 liters of Insecticide 2, and 60 litres of Insecticide 3, with a total budget of RM 157,397.17. Meanwhile, BL was allocated 8 personnel and RM 104,931.44. These allocations are not influenced by any algorithmic optimization based on dengue case severity or variability.

Table 4: Baseline Resource Allocation

District	# Mukims	Manpower	Insecticide 1	Insecticide 2	Insecticide 3	Budget
BL	8	22	278.56	106.76	16.64	104,931.44
BB	8	14	67.52	14.40	10.00	52,465.72
KS	35	24	835.00	220.00	60.00	157,397.17
KM	16	34	939.00	191.00	36.00	157,397.17
KP	21	18	415.00	90.00	22.00	52,465.72
KL	16	26	574.75	225.40	7.50	157,397.17
LG	6	12	289.30	24.00	3.84	52,465.72
PT	11	18	51.34	0.00	0.00	52,465.72
PG	8	14	128.96	55.84	10.00	52,465.72
SK	4	16	80.21	0.00	0.00	52,465.72
YN	5	8	57.36	7.20	0.00	52,465.72
Total	138	206	3,717.00	934.60	165.98	944,383.00

Using Fitness Functions 1 and 2, Table 5 shows that the resource allocation became more refined, with minor adjustments observed in districts like KS, where manpower was reduced from 24 to 23, and budgetary requirements were slightly reduced. Similarly, other districts, such as Baling, retained their resource allocations, demonstrating that the overall adjustments were minimal yet positive. Notably, 137 out of 138 mukims received allocation, and the total area covered remained efficient, suggesting that moderate optimization was achieved. Although Fitness Functions 1 and 2 produced slight reductions in resource allocation, the impact was relatively modest. In essence, while there were small gains in efficiency, particularly in terms of budget reductions for KS, the algorithm did not significantly diverge from the original allocation.

Table 5: Resource Allocation by using Fitness Function 1 & 2

District	Allocated	Manpower	Insecticide 1	Insecticide 2	Insecticide 3	Budget (RM)
BL	8	22	278.56	106.76	16.64	104,931.44
BB	8	14	67.52	14.40	10.00	52,465.72
KS	**34**	**23**	**811.14**	**213.71**	**58.29**	**152,900.11**
KM	16	34	939.00	191.00	36.00	157,397.17
KP	21	18	415.00	90.00	22.00	52,465.72
KL	16	26	574.75	225.40	7.50	157,397.17
LG	6	12	289.30	24.00	3.84	52,465.72
PT	11	18	51.34	0.00	0.00	52,465.72
PG	8	14	128.96	55.84	10.00	52,465.72
SK	4	16	80.21	0.00	0.00	52,465.72
YN	5	8	57.36	7.20	0.00	52,465.72
Total	**137**	**205**	**3,693.14**	**928.31**	**164.27**	**939,885.93**

Table 6 shows the allocation output based on Fitness Function 3, which is centred on dengue case counts, and introduced more significant changes in resource distribution. For example, BB saw its manpower allocation reduced from 14 to 13, and its budget was cut from RM 52,465.72 to RM 48,093.58. KM also experienced reductions in insecticide and budget allocations. By prioritizing areas with higher case densities, Fitness Function 3 facilitated a more targeted approach to resource allocation. However, districts such as KS, which had higher case counts, maintained their original allocations, indicating that the function was most impactful in districts with fewer cases. Overall, Fitness Function 3 improved resource efficiency by adjusting allocations in response to dengue case densities, although it did not result in substantial optimization beyond reducing resources in lower-priority districts.

Table 6: Resource Allocation by using Fitness Function 3

District	Allocated	Manpower	Insecticide 1	Insecticide 2	Insecticide 3	Budget (RM)
BL	8	22	278.56	106.76	16.64	104,931.44
BB	**7**	**13**	**61.89**	**13.20**	**9.17**	**48,093.58**
KS	35	24	835.00	220.00	60.00	157,397.17
KM	**16**	**33**	**919.44**	**187.02**	**35.25**	**154,118.06**
KP	21	18	415.00	90.00	22.00	52,465.72
KL	16	26	574.75	225.40	7.50	157,397.17
LG	6	12	289.30	24.00	3.84	52,465.72
PT	11	18	51.34	0.00	0.00	52,465.72
PG	8	14	128.96	55.84	10.00	52,465.72
SK	4	16	80.21	0.00	0.00	52,465.72
YN	5	8	57.36	7.20	0.00	52,465.72
Total	**137**	**204**	**3,691.81**	**929.42**	**164.40**	**936,731.74**

Fitness Function 4, which incorporates the Rank Weighted Mean (RWM) approach using variance and standard deviation, provided a more comprehensive optimization model. High-priority areas like KS retained their resource allocations, whereas districts such as YN experienced notable reductions, with manpower decreasing and the budget reduced from RM 52,465.72 to RM 45,470.29. Similarly, districts like KL saw slight decreases in insecticide usage. Fitness Function 4's ability to factor in both the consistency of dengue cases and the severity of outbreaks allowed for a more strategic distribution of resources. Areas with more stable case counts saw justified reductions in resources, while regions with high variability or severe outbreaks maintained their original allocations.

Table 7: Resource Allocation by using Fitness Function 4

District	Allocated	Manpower	Insecticide 1	Insecticide 2	Insecticide 3	Budget (RM)
BL	8	22	278.56	106.76	16.64	104,931.44
BB	8	14	67.52	14.40	10.00	52,465.72
KS	35	24	835.00	220.00	60.00	157,397.17
KM	16	34	939.00	191.00	36.00	157,397.17
KP	21	18	415.00	90.00	22.00	52,465.72
KL	**16**	**25**	**562.78**	**220.70**	**7.34**	**154,118.06**
LG	6	12	289.30	24.00	3.84	52,465.72
PT	11	18	51.34	0.00	0.00	52,465.72
PG	8	14	128.96	55.84	10.00	52,465.72
SK	4	16	80.21	0.00	0.00	52,465.72
YN	**4**	**7**	**49.71**	**6.24**	**0.00**	**45,470.29**
Total	**137**	**204**	**3,697.38**	**928.94**	**165.82**	**934,108.45**

Conclusion

Fitness Functions 1 and 2 introduced modest improvements to resource allocation, particularly with small reductions in budget and insecticide use. However, these changes closely mirrored the original allocations, resulting in minimal overall optimization. Fitness Function 3, which incorporated dengue case counts, provided a more data-driven and targeted approach. This led to more noticeable improvements, especially in districts with fewer cases, where resources were reduced to reflect the lower demand. Despite these enhancements, Fitness Function 3 was still limited in addressing the variability of dengue cases. Fitness Function 4 demonstrated the most effective optimization by integrating both the severity and variability of dengue cases. Incorporating the Rank Weighted Mean (RWM), it allowed for a more balanced distribution of resources. This approach ensured that high-priority districts, like KS, received sufficient resources, while areas with stable but fewer cases, such as YN, saw appropriate reductions. In terms of resource efficiency, Fitness Function 4 outperformed the other fitness functions, optimizing resource use while maintaining broader coverage across districts.

The results highlight critical implications for healthcare logistics, particularly in optimizing the flow and use of resources for dengue management. Fitness Function 4 shows that integrating case severity and variability into allocation models enables more precise demand forecasting, ensuring resources such as insecticides, spraying equipment, and field teams are deployed where they are needed most. This approach reduces inefficiencies caused by blanket distribution, cuts down on excess inventory in low-demand areas, and prevents shortages in high-risk districts. From a logistics perspective, it enhances supply chain agility by aligning distribution with fluctuating case patterns, thereby improving response times and operational resilience. Moreover, it supports better budgeting and workforce planning, as resources can be scaled and mobilised more strategically. Importantly, the optimisation model offers a replicable framework that can be extended beyond dengue to strengthen healthcare logistics systems for other infectious diseases and public health emergencies.

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