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Modelling resource allocation in dengue management as Negative Binomial distribution-based model

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ABSTRACT

Dengue fever remains one of the most pressing public health challenges in tropical regions, with its rapid spread placing significant strain on healthcare resources. Efficient resource allocation is critical to mitigating outbreaks, particularly in areas with varying disease severity. This study presents an optimization framework that integrates Genetic Algorithms (GA) with the Negative Binomial distribution to enhance resource allocation for dengue management in Kedah, Malaysia, from 2011 to 2023. The model incorporates constraints on manpower, insecticides, and budget, with the objective of maximizing fogging coverage while prioritizing high-burden areas as classified by the Dengue Monitoring and Surveillance System (DMOSS). Three GA configurations were tested, varying population size, mutation rate, and crossover probability, and results were compared to the baseline allocation. The findings reveal that GA-based optimization outperforms static allocation strategies by directing more resources to high-severity districts, thereby increasing severity-weighted effective coverage. Among the tested configurations, the model with a population size of 100 (Trial c) achieved the highest fitness value (4.7743), covering 5,572.71 km² with 3,486.54 km² severity-weighted coverage. The results demonstrate the potential of combining probabilistic severity modeling with metaheuristic optimization to improve the efficiency and equity of dengue control interventions, offering a replicable approach for other vector-borne disease management contexts.

1. Introduction

Dengue fever, a debilitating illness caused by the dengue virus, presents a significant and growing threat to public health, especially in tropical and subtropical regions. The virus's transmission hinges on the activity of Aedes mosquitoes, notorious for their breeding habits in stagnant water. This makes

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densely populated urban areas particularly susceptible to outbreaks. According to the World Health Organization (WHO), dengue has ascended to one of the fastest-proliferating mosquito-borne diseases, with an estimated 390 million infections occurring globally each year [1]. This staggering figure underscores the substantial strain dengue places on healthcare systems worldwide, highlighting the urgency of optimizing resource allocation for effective dengue management. Such optimization is crucial in minimizing the disease's impact and bolstering the efficiency of outbreak response measures.

Navigating the complexities of effective resource allocation requires a nuanced understanding of a myriad of factors. These include the severity of the disease, population density, the capacity and infrastructure of local healthcare systems, and the dynamic nature of dengue transmission. Traditional resource allocation strategies often fall short, relying on static methods that fail to capture the fluid and unpredictable nature of outbreak dynamics [2]. In contrast, contemporary approaches increasingly prioritize innovative solutions that leverage advanced algorithms and data-driven insights. These cutting-edge methods hold promise for more accurately predicting and managing the spread of dengue, thereby enhancing the overall effectiveness of public health interventions. This study endeavors to address a notable gap in the current body of literature by systematically comparing various optimization models for resource allocation in dengue management. Specifically, it examines the efficacy of GA-based on statistical distribution models namely Negative Binomial distributions. By employing a comprehensive and multi-faceted approach, this research seeks to identify the most effective methods for resource distribution based on the severity of the disease. The ultimate goal is to contribute to the development of more efficient and targeted public health interventions, thereby enhancing the capacity to manage and mitigate the impact of dengue outbreaks.

2. Literature Review

Genetic Algorithms in Resource Optimization Genetic algorithms (GAs) have garnered widespread recognition for their efficacy in tackling intricate optimization challenges across various domains, such as operations research, engineering, and public health. Inspired by the principles of natural selection, GAs employ a population-based search strategy that enables the exploration of vast solution spaces with remarkable efficiency. Recent studies have underscored the potential of GAs in resource allocation for a range of public health crises, including disaster response and epidemic management [3][4].

In the realm of dengue management, GAs exhibits the capacity to optimize resource distribution by considering multiple criteria, such as disease severity, geographic distribution of cases, and availability of resources. The inherent flexibility of GAs facilitates the development of adaptive solutions that can accommodate the dynamic nature of outbreak patterns [5]. Moreover, the integration of GAs with machine learning techniques has shown considerable promise in enhancing the predictive accuracy of resource allocation models, thereby improving the overall effectiveness of public health interventions [6][7].

k-Nearest Neighbors in Epidemiology k-Nearest Neighbors (kNN) is a prominent supervised learning algorithm, celebrated for its straightforwardness and efficacy in both classification and regression tasks. Within the field of epidemiology, kNN has been utilized to forecast disease outcomes based on historical data, leveraging the proximity of cases within a multi-dimensional feature space [8][9]. Despite its strengths, kNN is not without limitations, particularly when applied to high-dimensional datasets where the curse of dimensionality may compromise accuracy [10]. In the context of dengue, were case data exhibit significant variability and spatial dependence, the effectiveness of kNN may be constrained. This necessitates the exploration of more robust modeling approaches, such as statistical distribution models, to achieve better predictive performance and resource allocation [11].

Recent advancements in research have highlighted RWM's potential in balancing trade-offs between resource availability and public health needs, providing a structured framework for decision-making in complex scenarios [12][13]. Nevertheless, the application of RWM in the management of infectious diseases, particularly in dengue resource allocation, remains relatively unexplored and merits further investigation.

Count data models, including the Negative Binomial and Geometric distributions, are instrumental in accurately capturing the underlying characteristics of disease incidence, particularly in scenarios marked by over-dispersion [14]. The Negative Binomial distribution is especially beneficial for modeling count data where the variance surpasses the mean, a common occurrence in dengue cases characterized by sporadic outbreaks and variable severity [4][15].

The Geometric distribution, which models the number of trials until the first success, is also applicable in understanding the interval until the first reported case in an outbreak. Incorporating these statistical models into resource allocation frameworks has demonstrated improved predictive accuracy and enhanced the allocation of healthcare resources during dengue outbreaks [16][17]. This underscores the necessity of integrating statistical methodologies with machine learning models to optimize public health responses effectively [18].

While numerous studies have delved into optimization methods within the realm of public health, there is a notable scarcity of comprehensive comparisons between different models for resource allocation specifically targeting dengue management. Prominent works have employed machine learning techniques to predict disease outbreaks and optimize resource distribution, setting the stage for more advanced approaches [19][20]. For instance, [21] delved into the potential of ensemble machine learning methods for predicting dengue incidence, underscoring the necessity of integrating predictive models within resource allocation frameworks.

Expanding on this foundation, [22] explored the optimization of vector control strategies through a multi-objective genetic algorithm, illustrating the critical role of resource allocation efficiency in managing mosquito populations. Although these studies offer invaluable insights, they fall short of providing a comparative analysis of machine learning models alongside statistical distribution methods—a gap this paper aims to address [1][23].

The fusion of statistical models with machine learning techniques has demonstrated considerable promise in enhancing healthcare resource allocation across diverse scenarios ([23][24]. Nevertheless, there remains a pressing need for a comprehensive understanding of how these integrated models can be effectively applied to dengue-specific resource allocation. This research presents an opportunity to fill this void by systematically evaluating the performance of different optimization models.

3. Methodology
3.1 Data Processing

The data used in this study was collected from various mukims and districts, including the number of dengue cases, manpower availability, insecticides, and budget for resource allocation. Severity was calculated using historical case data, population density, and health infrastructure in each area. Data preprocessing involved normalization and handling of missing values to ensure accuracy in model performance.

The kNN method computed severity based on the distance to the nearest neighbors, which can be influenced by the distribution of cases in adjacent areas. RWM assigned weights to areas based on disease severity and population density, allowing for a nuanced understanding of resource needs.

Number of dengue cases registered from 2011 to 2023 for State of Kedah were collected, with the severity level of each district differs. The severity level is determined by DMOSS classification as shown in Table 1. By taking dengue cases from 2011 to 2023, only Kuala Muda (KM) is categorized as district with high burden of dengue cases, followed by Baling (BL), Kota Setar (KS), Kubang Pasu (KB) and Kulim (KL)as districts with moderate burden of dengue cases (Refer Table II). The rest of districts were categorized as low burden (Bandar Baharu (BB), Langkawi (LG), Padang Terap (PT), Pendang (PG), Sik (SK) and Yan (YN)). The data on dengue occurrences were collected Referring to DMOSS Orientated Dengue Preventive Activities, the locality classification is as shown in Table 2. In 2023, according to the number of dengue cases registered in that particular year, UKPBV, KKM concluded that Kuala Muda (KM), Kulim (KL) and Kota Setar (KS) were categorized as districts with high burden of dengue cases, then Baling, Kubang Pasu (KP) and Langkawi (LG) as moderate burden. The rest of districts were categorized as low burden (Bandar Baharu (BB), Padang Terap (PT), Pendang (PG), Sik (SK) and Yan (YN)) [25].

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 District

District	*BL*	*BB*	*KS*	*KM*	*KP*	*KL*	*LG*	*PT*	*PG*	*SK*	*YN*
Severity	Moderate	Low	Moderate	High	Moderate	Moderate	Low	Low	Low	Low	Low

**Data of cases from ME 1 2011 to ME52 2023*
**total weeks from year 2011 to 2023 = 678 weeks*
**(total accumulated cases from year ME 1 2011 to ME 52 2023/cumulative number of weeks)*

3.2 The Model

The optimization problem included constraints on the available manpower, insecticides, and budget. These resources were distributed across districts and mukims based on the output of each model, and the GA optimized the allocation by minimizing a weighted objective function that balanced case severity with resource capacity. The fitness function used was formulated to minimize the total dengue cases while considering the constraints of available resources. This approach aimed to reflect real-world priorities and ensure that high-severity areas received adequate resources.
Objective function: To maximize the coverage area (in km^2) of fogging activities in each area within each district.

Table 3
List of districts, i

District	*i*
Baling	1
Bandar Baharu	2
Kota Setar	3
Kuala Muda	4
Kubang Pasu	5
Kulim	6
Langkawi	7
Padang Terap	8
Pendang	9
Sik	10
Yan	11

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:
$Maximize\ Z = \sum_{i=1}^{11} x_{ij}$ (Eq 1)
Subject to the following constraints:
Constraints of single-objective optimization

Total manpower at each district, $\boldsymbol{A_i}$: (Eq 2)

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

Total manpower constraint:
$\boldsymbol{A_1 + A_2 + \cdots + A_{11} \leq 206}$ (Eq 3)

District-specific insecticide constraints**:**

$\boldsymbol{S_{ik} \leq Stock\ of\ insecticide\ type\ k\ in\ District\ i}$ (Eq 4)

$\boldsymbol{k =}$ **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:

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

Total stock of insecticides constraint:

$$\boldsymbol{S_1 + S_2 + \cdots + S_{11} \leq 4817.58\ litres} \quad \text{(Eq 5)}$$

Budget constraints, $\boldsymbol{C_i}$: (Eq 6)

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

3.3 The GA Setting

The Genetic Algorithm (GA) was configured as specified in Table 4. These parameter choices are based on prior research indicating their effectiveness in convergence speed and optimization quality. The population size was selected to ensure diversity in the solution space while maintaining computational efficiency. The number of runs was increased to capture variability in results and ensure robust conclusions. Maximum iterations were set to allow adequate exploration of the solution space. The mutation rate was varied to prevent premature convergence and to encourage exploration, while the crossover rate was adjusted to enhance the mixing of genetic information among solutions. Assume that the number of dengue cases in each mukims follows the negative binomial distribution, the Parameters setting for Negative binomial distribution.

The Negative Binomial distribution is particularly effective for count data where variance exceeds the mean, making it a suitable choice for dengue case data characterized by outbreaks of varying intensity [26]. The choice of severity calculation method impacts resource allocation strategies, as different models may emphasize different aspects of the data, leading to varying recommendations for resource distribution.

Table 4
GA Setting

Parameter tested	Arguments in R	Description	#
Type of GA	type	The type of genetic algorithm to be run depending on the nature of decision variables.	"binary" for binary representations of decision variables.
Fitness Function	fitness	The fitness function, any allowable R function which takes as input an individual string representing a potential solution and returns a numerical value describing its ``fitness''.	R5
Number of bits	nBits	A value specifying the number of bits to be used in binary encoded optimizations.	Number of rows in the dataset; nrow(dataset)
Number of population	popSize	An R function for randomly generating an initial population.	(10,50,100)
Maximum iteration	maxiter	The maximum number of iterations to run before the GA search is halted.	4000
Number of runs	run	The number of consecutive generations without any improvement in the best fitness value before the GA is stopped.	4000
Probability of mutation	pmutation	The probability of mutation in a parent chromosome. Usually, mutation occurs with a small probability, and by default is set to 0.1.	0.1, 0.2, 0.3, 0.4, 0.5
Probability of crossover	pcrossover	The probability of crossover between pairs of chromosomes. Typically, this is a large value and by default is set to 0.8.	0.1, 0.2, 0.3, 0.4, 0.5

The fitness function used in the GA-based Negative Binomial model is designed to assess the efficiency of resource allocation across mukims based on the severity of dengue outbreaks. The process begins by ranking the mukims according to the number of dengue cases, where higher case numbers receive a higher priority (lower rank number). These ranks are inverted and normalized into weights, where mukims with more severe outbreaks (higher case counts) are given larger weights, ensuring that resources are proportionally allocated based on severity. The Negative Binomial distribution is applied to model the severity of dengue in each mukim. This distribution is well-suited for count data with over-dispersion, a common characteristic of dengue outbreaks where variance exceeds the mean. The *size_param* in the distribution represents the number of successes required, and the *prob_param* is the probability of success on each trial. The function uses these parameters to generate random values representing the severity of outbreaks in each mukim.

In terms of resource allocation, the fitness function calculates the total coverage, manpower, insecticide (three types), and budget allocated to each district. Resources are distributed based on the severity-weighted coverage, ensuring that high-severity mukims receive more attention. The function also imposes constraints on the total manpower (206), insecticide (different limits for each type), and budget (RM 944,383). If any allocation exceeds these limits, the fitness function returns -

Inf, penalizing invalid solutions. Ultimately, the fitness value returned is the severity-weighted total coverage, with higher values representing more efficient and effective resource allocations.

5. Results and Discussion

The original resource allocation (refer Table 5) 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, Kota Setar 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, Baling 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 5
Original Resources Allocation

District	# Mukims	Manpower	Insecticide 1	Insecticide 2	Insecticide 3	Budget
Baling	8	22	278.56	106.76	16.64	104,931.44
Bandar Baharu	8	14	67.52	14.40	10.00	52,465.72
Kota Setar	35	24	835.00	220.00	60.00	157,397.17
Kuala Muda	16	34	939.00	191.00	36.00	157,397.17
Kubang Pasu	21	18	415.00	90.00	22.00	52,465.72
Kulim	16	26	574.75	225.40	7.50	157,397.17
Langkawi	6	12	289.30	24.00	3.84	52,465.72
Padang Terap	11	18	51.34	0.00	0.00	52,465.72
Pendang	8	14	128.96	55.84	10.00	52,465.72
Sik	4	16	80.21	0.00	0.00	52,465.72
Yan	5	8	57.36	7.20	0.00	52,465.72
Total	**138**	**206**	**3,717.00**	**934.60**	**165.98**	**944,383.00**

Count data models, such as the Negative Binomial and Geometric distributions, are essential for accurately capturing the nature of disease incidence, particularly in situations where over-dispersion occurs [14]. In this study, a Genetic Algorithm (GA) approach was applied to optimize resource allocation across districts and mukims, incorporating the Negative Binomial distribution to account for dengue severity. This approach prioritizes high-risk areas using probabilistic severity scores, enhancing the efficiency of resource distribution. A total of 75 trials were conducted, varying population sizes (10, 50, 100), mutation rates, and crossover probabilities (ranging from 0.1 to 0.5), with each trial run for 4000 iterations. The best-performing model for each population size, based on the highest fitness value, was selected, resulting in the top 3 models (a, b and c).

Table 6
Allocation using Negative Binomial (three specifications 1, b and c)

	Negative Binomial – using Fitness Function R5_nb		
Trial	**a**	**b**	**c**
Population Size	10	50	100
Max Iterations	4000	4000	4000
Number of runs	4000	4000	4000
Probability of mutation	0.1	0.4	0.3
Probability of crossover	0.5	0.5	0.4
Total Mukims Allocated	67 out of 138 mukims	77 out of 138 mukims	80 out of 138 mukims
Total Area Covered (km²)	4,611.34 km²	4,391.54 km²	5,572.71 km²
Total Effective Coverage Area (km²)	3,198.28 km²	2,976.08 km²	3,932.10 km²
Total Severity-Weighted Effective Coverage Area (km²)	2,624.08 km²	2,637.50 km²	3,486.54 km²
Total Manpower	104 people	108 people	114 people
Total Insecticide 1 (litres)	1,893.99 litres	2,041.32 litres	2,138.32 litres
Total Insecticide 2 (litres)	481.06 litres	526.54 litres	541.75 litres
Total Insecticide 3 (litres)	84.69 litres	93.56 litres	99.43 litres
Total Budget (RM)	RM 474,388.90	RM 518,283.50	RM 527,496.30
Time-elapsed (seconds)	69.11 seconds	259.49 seconds	452.54 seconds
Final Fitness Function Value	3.9428	4.3501	4.7743

Table 6 presents the resource allocation for each district for Trial a when using a population size of 10, mutation probability of 0.1, and crossover probability of 0.5 in the GA optimization. In this model, districts such as Kota Setar received significant resources, including 16 manpower, 381.71 litres of Insecticide 1, and a budget of RM 71,952.99. In contrast, districts like Sik received minimal resources, with just 1 personnel and RM 13,116.43 in budget. In addition, there is no resources allocated to Yan district. This model reflects a moderate allocation effort based on the severity of dengue outbreaks across the districts.

Table 6
Resources Allocation by using Fitness Function Trial a (popsize=10, pmutation=0.1, pcrossover=0.5)

District	Allocated	Manpower	Insecticide 1	Insecticide 2	Insecticide 3	Budget
Baling	5	14	174.10	66.73	10.40	65,582.15
Bandar Baharu	7	12	59.08	12.60	8.75	45,907.51
Kota Setar	16	11	381.71	100.57	27.43	71,952.99
Kuala Muda	9	19	528.19	107.44	20.25	88,535.91
Kubang Pasu	7	6	138.33	30.00	7.33	17,488.57
Kulim	9	15	323.30	126.79	4.22	88,535.91
Langkawi	4	8	192.87	16.00	2.56	34,977.15
Padang Terap	6	10	28.00	0.00	0.00	28,617.67
Pendang	3	5	48.36	20.94	3.75	19,674.65
Sik	1	4	20.05	0.00	0.00	13,116.43
Yan	0	0	0	0	0	0
Total	**67**	**104**	**1,893.99**	**481.06**	**84.69**	**474,388.92**

Next, Table 7 shows the results from using Trial b of a population size 50, a mutation probability of 0.4, and a crossover probability of 0.5. Here, the overall resource allocation is more evenly distributed, with notable increases in manpower for districts like Kota Setar (24 personnel) and a larger budget (RM 107,929.49). Sik, on the other hand, receive smaller allocations. The increase in population size and mutation rate appears to provide more exploration of potential resource distributions.

Table 7
Resources Allocation by using Fitness Function Trial b (popsize=50, pmutation=0.4, pcrossover=0.5)

District	Allocated	Manpower	Insecticide 1	Insecticide 2	Insecticide 3	Budget
Baling	3	8	104.46	40.04	6.24	39,349.29
Bandar Baharu	5	9	42.20	9.00	6.25	32,791.08
Kota Setar	24	16	572.57	150.86	41.14	107,929.49
Kuala Muda	7	15	410.81	83.56	15.75	68,861.26
Kubang Pasu	9	8	177.86	38.57	9.43	22,485.31
Kulim	10	16	359.22	140.88	4.69	98,373.23
Langkawi	4	8	192.87	16.00	2.56	34,977.15
Padang Terap	4	7	18.67	0.00	0.00	19,078.44
Pendang	6	11	96.72	41.88	7.50	39,349.29
Sik	1	4	20.05	0.00	0.00	13,116.43
Yan	4	6	45.89	5.76	0.00	41,972.58
Total	**77**	**108**	**2,041.32**	**526.54**	**93.56**	**518,283.54**

Finally, in Trial c, this model uses a larger population size of 100, with mutation and crossover probabilities of 0.3 and 0.4, respectively (refer Table 8). The results show a substantial allocation of resources to high-severity areas. For example, Kota Setar is allocated 23 personnel, 548.71 litres of Insecticide 1, and a budget of RM 103,432.43. Smaller districts such as Sik and Yan receive fewer resources. This model demonstrates a more focused allocation, with larger districts receiving the majority of resources, which may reflect their higher disease severity.

Table 8
Resources Allocation by using Fitness Function Trial c (popsize=100, pmutation=0.3, pcrossover=0.4)

District	Allocated	Manpower	Insecticide 1	Insecticide 2	Insecticide 3	Budget
Baling	3	8	104.46	40.04	6.24	39,349.29
Bandar Baharu	5	9	42.20	9.00	6.25	32,791.08
Kota Setar	23	16	548.71	144.57	39.43	103,432.43
Kuala Muda	9	19	528.19	107.44	20.25	88,535.91
Kubang Pasu	13	11	256.90	55.71	13.62	32,478.78
Kulim	9	15	323.30	126.79	4.22	88,535.91
Langkawi	3	6	144.65	12.00	1.92	26,232.86
Padang Terap	4	7	18.67	0.00	0.00	19,078.44
Pendang	6	11	96.72	41.88	7.50	39,349.29
Sik	2	8	40.11	0.00	0.00	26,232.86
Yan	3	5	34.42	4.32	0.00	31,479.43
Total	**80**	**114**	**2,138.32**	**541.75**	**99.43**	**527,496.27**

When comparing the baseline resource allocation with the GA-optimized models above, the differences are evident in both manpower and resource distribution. For example, Kota Setar originally received 24 personnel, but under the GA optimization, it was allocated 16 (Trial a), 24 (Trial b), and 23 (Trial c). The changes in insecticide and budget allocations are similarly varied. The differences in resource allocation between the baseline and GA-optimized models can be attributed to the algorithm's prioritization of districts based on disease severity, as modelled by the Negative Binomial distribution. The GA is designed to allocate resources more efficiently, focusing on districts with higher dengue severity, which explains why larger and more severely affected districts like Kota Setar and Kuala Muda consistently receive more resources than smaller or less severely impacted districts such as Sik or Yan. Additionally, the variation in population size and mutation/crossover probabilities affects how thoroughly the GA explores different allocation scenarios, leading to variations in the resource distribution.

In conclusion, the GA-based Negative Binomial model effectively reallocates resources based on dengue severity, optimizing the distribution compared to the baseline allocation. Across the models, larger population sizes lead to more efficient and targeted resource allocation, particularly in districts with higher dengue case counts. Trial c, with a population size of 100, performed the best, distributing more resources to high-severity areas like Kota Setar while minimizing waste in lower-severity districts. This shows the importance of balancing population size, mutation, and crossover probabilities to achieve optimal resource allocation in response to disease outbreaks.

6. Conclusion and Recommendation

This study demonstrates that integrating Genetic Algorithms (GA) with the Negative Binomial distribution provides a robust and adaptive approach to dengue resource allocation in Kedah. By incorporating severity-based prioritization from DMOSS classifications, the model achieved higher severity-weighted coverage compared to conventional static allocation strategies. The results show that Trial C, with a GA population size of 100, yielded the highest optimization performance, balancing both geographical coverage and disease burden. These findings underscore the value of probabilistic modeling combined with metaheuristic optimization in enhancing the effectiveness of vector control measures, particularly in resource-constrained settings.

It is recommended that health authorities adopt the GA-based allocation model as part of routine dengue control planning to ensure that resources are deployed more effectively to areas with the highest disease burden. Previous studies have shown that optimization methods, such as Genetic Algorithms, can significantly improve the efficiency of health resource allocation, particularly in vector control operations [27]. To maximize its impact, the proposed model should be integrated with real-time DMOSS surveillance data, enabling dynamic adjustments to manpower and insecticide allocation as outbreak conditions evolve. Similar integration of optimization tools with real-time disease monitoring has been demonstrated to improve responsiveness and targeting in dengue prevention [7]. Regular reviews and tuning of GA parameters, such as population size, mutation rate, and crossover probability, are also necessary to maintain optimal performance under changing epidemiological and operational scenarios, in line with recommendations from computational optimization research [28]. Furthermore, this approach has the potential to be adapted for other vector-borne diseases, such as malaria or chikungunya, thereby extending its value as a decision-support tool in broader public health resource management [29].

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