Available online at http://scik.org
Commun. Math. Biol. Neurosci. 2025, 2025:69
https://doi.org/10.28919/cmbn/9256
ISSN: 2052-2541

MENU PLANNING USING MULTI-COMPLEX DIFFERENTIAL EVOLUTION ALGORITHM FOR WASTING CHILDREN

ADRIANA FANGGIDAE[1,*], YULIANTO TRIWAHYUADI POLLY[1], ANDREA STEVENS KARNYOTO[2,3], JUAN RIZKY MANNUEL LEDOH[1], CLARISSA ELFIRA AMOS PAH[1], ARFAN YEHESKIEL MAUKO[1], SINYO APRIL DETHAN[1], BENS PARDAMEAN[2,3]

[1]Department of Computer Science, Universitas Nusa Cendana, Kupang 85148, Indonesia

[2]Bioinformatics and Data Science Research Center, Bina Nusantara University, Jakarta 11480, Indonesia

[3]Computer Science Department, BINUS Graduate Program - Master of Computer Science Bina Nusantara University, Jakarta 11480, Indonesia

Abstract: Despite Indonesia's stable economic growth, child wasting remains high, particularly in Nusa Tenggara Timur (NTT) Province, reflecting a disparity between economic progress and public health. The complexity of this issue is exacerbated by the low level of women's education in NTT, while climatic factors and soil conditions further impact food availability. We used the Multi-Complex Differential Evolution algorithm to serve as an effective and efficient tool for mothers in planning a diverse selection of nutritious meals for their children based on food availability and parental economic capacity. The algorithm analyses local food resources and suggests meal plans that maximise nutritional value within available ingredients. Optimising food combinations ensures children receive balanced nutrition, addressing deficiencies contributing to child wasting. The findings indicate that this algorithm performs well with a population size of 30 and a maximum of 1,000 iterations using the DE/rand/1 mutation function. Moreover, with these parameters, the algorithm generates various healthy meal plans that meet multiple constraints while ensuring a short execution time.

Keywords: wasting child; menu planning; differential evolution; nusa tenggara timur; algorithm.

2020 AMS Subject Classification: 92C60.

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[*]Corresponding author

E-mail address: adrianafanggidae@staf.undana.ac.id

Received March 20, 2025

1. INTRODUCTION

The development of human resources has been Indonesia's national priority since 2019 [1]. This development is key to gaining a competitive edge globally and achieving national prosperity. Ensuring a healthy, intelligent, and productive generation emerges is essential to cultivating high-quality human resources. This effort begins within the family environment by guaranteeing that children receive adequate nutritional intake. Proper nutrition in children is crucial in preventing malnutrition, which seriously threatens health and well-being [2].

According to The State of Food Security and Nutrition in the World report released by the Food and Agriculture Organization (FAO) for the 2019–2021 period [3], Indonesia ranked first in Southeast Asia, with 17.7 million people experiencing undernutrition, accounting for approximately 6.5% of the total national population. Children aged 0–60 months are the most vulnerable group to nutritional issues, including wasting (wasted and severely wasted). Wasting refers to a condition in which a child has a low weight relative to height [4]. Based on the Indonesia Nutrition Status Survey (SSGI) in 2022, the national wasting rate in Indonesia reached 7.7%. Maluku Province recorded the highest wasting rate at 11.9%, while Bali Province had the lowest at 2.8% [5]. According to the 2022 report from Statistics Indonesia (BPS) [6], the wasting rate in Nusa Tenggara Timur (NTT) Province was 8.5%, which increased to 9% in 2023. Wasting children differs from stunting. Stunting occurs when children experience prolonged periods of inadequate nutrition, particularly during the first 1,000 days of life—from conception to age two [7]-[10]. A characteristic of wasting children is a low weight-for-height ratio, a critical indicator of acute malnutrition. This condition often results from insufficient dietary intake, frequent infections, or both, and it can have severe consequences for a child's health and development.

Early prevention of wasting can be achieved through routine growth monitoring at community health posts (posyandu) and self-monitoring at home [11]. Home monitoring requires the active role of mothers in ensuring adequate child nutrition. Maternal nutrition knowledge is crucial for fulfilling the dietary intake to support optimal growth and development, particularly during the critical brain, bone, and immune system development periods. However, the level of women's education in NTT remains low. According to the 2023 Statistics Indonesia (BPS) report [12], 31.35% of women in NTT have only completed primary education, while 24.53 % have never attended school or did not complete primary education, totalling over 50%. Another challenge is the unfavourable climate and soil conditions in NTT, which hinder agricultural productivity, limit crop diversification, and reduce the variety of food sources available from the agriculture and livestock sectors.

Empat Sehat Lima Sempurna (Four Healthy, Five Perfect) was introduced in 1952 as a guideline for daily nutritional fulfilment in Indonesia. This dietary model emphasises the consumption of staple foods, protein sources, vegetables, fruits, and milk. However, it primarily focuses on nutrient completeness (carbohydrates, proteins, fats, vitamins, and minerals) without specifying the appropriate portion sizes for each food group. This concept has now been replaced by the *Balanced Nutrition Guidelines*, which emphasise nutrient adequacy and consider appropriate portions based on individual needs. In applying the balanced nutrition concept, mothers must be capable of designing proper meal plans, ensuring a well-balanced combination of food ingredients and appropriate portioning. Additionally, it is crucial to source food ingredients from the local environment to minimise financial burdens on households.

In recent years, optimisation algorithms have become increasingly prevalent in meal planning. Various health institutions have provided extensive information and data to support this development. Research on diet menu planning using the Evolutionary Algorithm (EA) NSGA-II (Elitist Non-Dominated Sorting Genetic Algorithm) [13] has demonstrated that computers can generate optimal 21-day meal plans based on dietary recommendations in a significantly shorter time than human professionals. Another study [14] applied a deterministic method and two metaheuristic methods for meal planning in obese children aged 4–18. The results showed that within a short time, metaheuristic methods successfully generated a weekly meal plan that met the dietary requirement of consuming meat and its substitutes three times per week. Furthermore, research utilising EA NSGA-III [15] for diet menu planning produced optimal daily meal plans based on individual preferences, age, gender, and body mass index. Additionally, a study on school meal planning [16] that adhered to Brazilian government requirements and employed the EA Genetic Algorithm (GA) successfully generated a five-day meal plan in just 60 seconds.

Meal planning is a multi-complex optimisation problem. The Differential Evolution (DE) algorithm is a straightforward yet effective EA that optimises simple and complex functions [17]. Several studies [18]-[21] have demonstrated that the DE algorithm outperforms other optimisation methods, including Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and GA, in finding optimal solutions for various combinatorial optimisation problems, thermal power generation input-output characteristics, academic scheduling, and transportation cost minimisation.

The optimisation problem in balanced nutrition meal planning for children aims to maximise the portion of each nutritional component presented in the "Isi Piringku" framework. "Isi Piringku" is a nutrition education program developed by the Ministry of Health of the Republic of Indonesia to provide guidelines on healthy portions in a single plate to meet balanced nutritional needs. This problem is fascinating because the list of food ingredients is sourced from local NTT products and can be adapted to parental preferences and economic capacity. Additionally, meal planning considers the ideal portion sizes to prevent undernutrition and overnutrition. This study employs a multi-objective and multi-constraint DE algorithm to determine a diverse and feasible combination of food ingredients for balanced nutrition meal planning. The contributions of this research include:

– Developed a system to assist mothers in efficiently planning nutritious and diverse meals.
– Created meal plans utilising readily available ingredients for parents.
– Choose the DE mutation variant that offers the most effective solution.

Overall, the findings indicate that the DE/rand/1 mutation function, with a population size of 30 and a maximum of 1,000 iterations, produces the highest number of meal variations with an average computation time of 5.52 seconds. Furthermore, the generated meal plans exhibit greater diversity.

2. Materials and Method

Dataset

We used food ingredient data and nutritional content sourced from the Ministry of Health of the Republic of Indonesia [22] and a website accessed on January 11, 2025 (https://nilaigizi.com/). Additional data from various sources are also included in this article and presented in several tables. The data is publicly available, which provides transparency and reproducibility for scientists.

Research Design

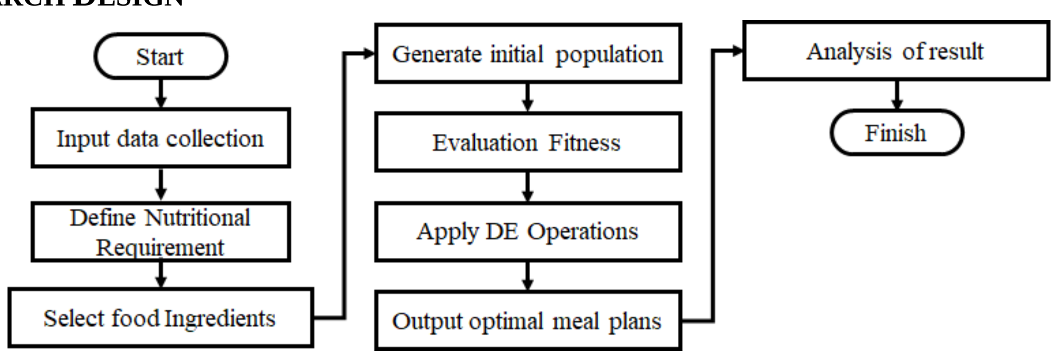

Figure 1. Research process

Figure 1 shows the process of our research. First, we collect nutritional data from the Ministry of Health and other sources to create optimal meal plans for children aged 12 to 60 months, focusing on food availability and nutritional requirements. We then calculate the daily energy, protein, fat, carbohydrate, and fibre needs based on the children's age, weight, and height. Next, we identify available food ingredients, categorising them into staple foods, protein sources, and vegetables. We initialise the Differential Evolution (DE) algorithm with parameters such as a population size of 30 and a maximum of 1,000 iterations, selecting the DE/rand/1 mutation function. Using these ingredients, we generate initial meal combinations. Each combination is evaluated for nutritional adequacy, portion size constraints, and ingredient diversity. The DE algorithm then applies mutation, crossover, and selection operations to create and refine new meal combinations, repeating this process for up to 1,000 iterations. Finally, we present the best meal plans that meet the children's nutritional needs and ingredient availability, ensuring a diverse and adequate diet that complies with nutritional guidelines. These meal plans are nutritious, engaging, and varied, providing a delightful dining experience for the children.

NUTRITION

The nutritional status of toddlers is measured based on age, body weight (W), and height (H). Body weight reflects body mass highly sensitive to sudden changes, such as decreased food intake. On the other hand, height is influenced by long-term nutritional intake. The body weight-to-height index assesses a child's health, growth, and nutritional status. The classification of nutritional status based on the W/H ratio is categorised as shown in Table 1.

Table 1. Thresholds for Nutritional Status of Children Aged 0–60 Months [23]

Index	**Nutritional Status Category**	**Threshold Z-score *)**
Weight-for-Height (W/H)	Severely wasted	< -3.0 SD
	Wasted	-3.0 SD to < -2.0 SD
	Normal	-2.0 SD to +1.0 SD
	Possible risk of overweight	> +1.0 SD to +2.0 SD
	Overweight	> +2.0 SD to +3.0 SD
	Obese	> +3.0 SD

*) SD refers to the Standard Deviation

Children enjoy engaging in physical activities that require energy. Maintaining a balance between energy intake and expenditure is essential to maintain a child's ideal weight (Y). Energy (E) is derived from macronutrients, namely carbohydrates (C), fats (L), and proteins (P).

Carbohydrates serve as an energy source, consisting of digestible carbohydrates in the form of glucose and starch and indigestible carbohydrates in fibre. Fats function as solvents for specific vitamins (A, D, E, K) and help maintain the immune system. Proteins provide essential amino acids for metabolism, muscle formation, bone development, blood production, and the maintenance of various organs. Children's nutritional requirements for energy, carbohydrates, fats, proteins, and fibre are detailed in Table 2.

Table 2. Daily Energy, Carbohydrate, Fat, and Protein Requirements for Children Aged 12–60 Months

Energy *) (kcal)		**Carbohydrates **) (g)**	**Fat **) (g)**	**Protein**) (g)**
Male	**Female**			
(100)Y_{min}-(100)Y_{max}	(90)Y_{min}-(90)Y_{max}	60% - 75% of energy requirements	15% - 25% of energy requirements	10% - 15% of energy requirements

*) Y_{min} is set at -2.0 SD, and Y_{max} is set at +1.0 SD for the normal nutritional status based on the W/H Standard [23]

**) Source [24]

Dietary fibre (Q) is abundant in vegetables and fruits; however, children tend to dislike vegetables. Nevertheless, they can consume fruits in large quantities and more frequently. Due to natural and climatic factors in NTT, fruits can only be harvested at certain times of the year. Therefore, this study excludes fruits, and the children's minimum fibre requirement is set at 1.5 grams per day.

DIFFERENTIAL EVOLUTION ALGORITHM

The Differential Evolution (DE) algorithm falls under Evolutionary Algorithms (EA), employing mutation, crossover, and selection mechanisms. DE offers several advantages over other evolutionary algorithms, including a simple structure, fast convergence, ease of use, high speed, and robustness [25], [26]. The implementation of the DE algorithm [27], [28]:

- Initialisation

$$X_{i,j}^{t} = Lb + rand[0,1](Ub - Lb) \tag{1}$$

- Mutation

  In the study [29], it was stated that there are four mutation variants in the DE algorithm that produce competitive results when tested on 13 benchmark functions. Two of them are:

  DE/rand/1:

$$V_{i}^{t} = X_{r_1}^{t} + F(X_{r_2}^{t} - X_{r_3}^{t}) \tag{2}$$

DE/best/1:

$$V_i^t = X_{best}^t + F(X_{r_1}^t - X_{r_2}^t) \quad (3)$$

- Crossover

$$U_{i,j}^t = \begin{cases} V_{i,j}^t & rand_{i,j}[0,1] \leq Cr \text{ } or \text{ } j = k \\ X_{i,j}^t & otherwise \end{cases} \quad (4)$$

- Selection

$$X_i^{t+1} = \begin{cases} U_i^t & f(U_i^t) \leq f(X_i^t) \\ X_i^t & otherwise \end{cases} \quad (5)$$

Two parameters, *F* and *Cr* = 0.5 [21], [28].

MENU PLANNING FORMULATION

In the menu planning problem, there is a set of food ingredients from which a subset is selected to create an optimal meal composition regarding nutrition while ensuring that portion constraints and nutritional requirements are not violated.

- The solution variables for staple foods (*U*), protein sources (*M*), and vegetables (*N*) are in integer form.
- Constraint function
  1. Restricting the intake of *U*, *M*, and *N* in grams per day, as presented in Equation (6).

$$\begin{gathered} 240 \leq U \leq 450 \\ 60 \leq M \leq 300 \\ 180 \leq N \leq 240 \end{gathered} \quad (6)$$

  2. Restricts the nutritional intake from all food ingredients included in "Isi Piringku," as shown in Equation (7).

$$\begin{gathered} E_{B_{min}} = \begin{cases} 100 * Y_{min} & Male \\ 90 * Y_{min} & Female \end{cases} \\ E_{B_{max}} = \begin{cases} 100 * Y_{max} & Male \\ 90 * Y_{max} & Female \end{cases} \\ E_{B_{min}} \leq E_O \leq E_{B_{max}} \\ \frac{60\% * E_{B_{min}}}{4} \leq C_O \leq \frac{75\% * E_{B_{max}}}{4} \\ \frac{15\% * E_{B_{min}}}{9} \leq L_O \leq \frac{25\% * E_{B_{max}}}{9} \\ \frac{10\% * E_{B_{min}}}{4} \leq P_O \leq \frac{15\% * E_{B_{max}}}{4} \end{gathered} \quad (7)$$

where *B* represents the required nutrients, and *O* represents the nutrient intake

- Objective function
  1. Minimising violations caused by nutrient intake exceeding the required amount can be observed in Equation (8). The optimal fitness value is $f_{obj1} = 0$.

$$E_Z = \begin{cases} 0 & E_{B_{min}} \le E_O \le E_{B_{max}} \\ 1 & else \end{cases}$$

$$C_Z = \begin{cases} 0 & C_{B_{min}} \le C_O \le C_{B_{max}} \\ 1 & else \end{cases}$$

$$L_Z = \begin{cases} 0 & L_{B_{min}} \le L_O \le L_{max} \\ 1 & else \end{cases}$$

$$P_Z = \begin{cases} 0 & P_{B_{min}} \le P_O \le P_{B_{max}} \\ 1 & else \end{cases}$$

$$Q_Z = \begin{cases} 0 & Q_O \ge 1.5 \\ 1 & else \end{cases}$$

$$f_{obj1_{min}} = E_Z + C_Z + L_Z + P_Z + Q_Z \tag{8}$$

  where Z represents the violation.

  2. Maximising the nutrition from all food ingredients included in "Isi Piringku" can be achieved if the difference between O and B_{max} is minimal, as described in Equation (9). The optimal fitness value is the minimum f_{obj2}.

$$f_E = \begin{cases} -\left(E_O - E_{B_{max}}\right) & E_{B_{min}} \le E_O \le E_{B_{max}} \\ 1{,}000 & else \end{cases}$$

$$f_C = \begin{cases} -\left(C_O - C_{B_{max}}\right) & C_{B_{min}} \le C_O \le C_{B_{max}} \\ 1{,}000 & else \end{cases}$$

$$f_L = \begin{cases} -\left(L_O - L_{B_{max}}\right) & L_{B_{min}} \le L_O \le L_{B_{max}} \\ 1{,}000 & else \end{cases}$$

$$f_P = \begin{cases} -\left(P_O - P_{B_{max}}\right) & P_{B_{min}} \le P_O \le P_{B_{max}} \\ 1{,}000 & else \end{cases}$$

$$f_Q = \begin{cases} -(Q_O - 1.5) & Q_O \ge 1.5 \\ 1{,}000 & else \end{cases}$$

$$f_{obj2_{min}} = f_E + f_C + f_L + f_P + f_Q \tag{9}$$

Where:

$$E_O = E_U + E_M + E_N$$

$$C_O = C_U + C_M + C_N$$

$$L_O = L_U + L_M + L_N$$

$$P_O = P_U + P_M + P_N$$

$$Q_O = Q_U + Q_M + Q_N$$

3. RESULTS AND DISCUSSION

In this study, the developed system is designed for children aged 12 to 60 months. The raw food ingredients in the database consist of commonly available ingredients accessible to the community in NTT. The number of food ingredients per group in the database includes 40 types of staple foods, 54 protein sources, and 56 vegetables. The system is tested to determine population parameters, maximum iterations, and mutation functions and to evaluate its ability to generate menus that align with the predefined formulation.

The testing was conducted using data from a 15-month-old boy with a height of 90 cm and a weight of 10.5 kg. Based on this information, the child's nutritional requirements were calculated and presented in Table 3. Meanwhile, the menu selected by the parents is shown in Table 4.

Table 3. Daily Nutritional Intake Requirements

Ideal Body Weight (kg)		**Energy (kcal)**		**Protein (g)**		**Fat (g)**		**Carbohydrates (g)**		**Fibre (g)**
Min	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**
10.9	13.8	1,090	1,380	27.25	51.75	18.17	38.33	163.5	258.75	1.5

Table 4. Selected Food Ingredients

Case	**Food Ingredients**	**Menu Combination**
1	*U* = white rice[2], dried corn kernels [9] *M* = raw tofu[4], shortfin scad/kombong fish[30] *N* = moringa leaves[14], water spinach[37]	${}_2C_1({}_2C_1){}_2C_1= 8$
2	*U* = white rice[2], dried corn kernels [9], white sweet potato[26] *M* = raw tofu[4], shortfin scad/kombong fish[30], pure/raw soybean tempeh[5] *N* = moringa leaves[14], water spinach[37], white spinach[1]	${}_3C_1({}_3C_1){}_3C_1= 27$
3	*U* = white rice[2], dried corn kernels[9], white sweet potato[26], taro[24] *M* = raw tofu[4], Shortfin scad/kombong fish[30], pure/raw soybean tempeh[5], pigeon pea[61] *N* = moringa leaves[14], water spinach[37], white spinach[1], mustard greens[48]	${}_4C_1({}_4C_1){}_4C_1 = 64$
4	*U* = white rice[2], dried corn kernels[9], white sweet potato[26], taro[24], cassava[23] *M* = raw tofu[4], shortfin scad/kombong fish[30], pure/raw soybean tempeh[5], pigeon pea[61], commercial chicken egg[51] *N* = moringa leaves[14], water spinach[37], white spinach[1], mustard greens[48], yellow pumpkin[42]	${}_5C_1({}_5C_1){}_5C_1= 125$

The data in Table 3 serves as the basis for forming individuals with dimensional lengths corresponding to the number of possible menu combinations. For example, in Case 1, the dimensional length of each individual is 8, with an illustration of the dimensional values for each individual shown in Table 5. Based on these individual values, the nutritional value of each food item on the menu can be calculated, and the results are presented in Table 6. Individual 1 has the best fitness value, with a menu that meets the constraints, specifically Menu 1, 2, 3, and 4.

Table 5. Illustration of an Individual for Case 1

Individual 1																								
Menu	1			2			3			4			5			6			7			8		
Menu Index	9	4	37	9	4	14	9	30	37	9	30	14	2	4	14	2	4	37	2	30	14	2	30	37
Weight (g)	314	74	212	314	74	212	277	73	211	277	60	190	367	281	189	367	281	189	367	281	189	367	281	189
Individual 2																								
Menu	1			2			3			4			5			6			7			8		
Menu Index	9	4	37	9	4	14	9	30	37	9	30	14	2	4	14	2	4	37	2	30	14	2	30	37
Weight (g)	283	116	223	251	91	235	271	78	226	272	291	226	268	200	210	251	82	235	251	82	235	251	91	235

Table 6. Fitness Calculation for Each Individual in Table 5

Individual 1									
Menu	1	2	3	4	5	6	7	8	**Total**
Energy (kcal)	1,267.80	1,403.48	1,152.47	1,254.02	1,708.87	1,587.91	1,790.36	1,669.40	
Protein (g)	46.05	49.65	50.38	50.04	71.10	67.88	102.29	99.07	
Fat (g)	27.88	29.79	22.94	24.28	22.47	20.77	14.04	12.34	
Carbohydrate (g)	225.83	247.88	199.64	218.58	312.23	292.58	309.98	290.33	
Fiber (g)	11.15	24.29	10.31	21.67	16.23	4.51	16.23	4.51	
Fitness 1	0	0	0	0	1	1	1	1	4
Fitness 2	101.64	111.42	114.66	125.30	1,000	1,000	1,000	1,000	4,453.02
Individual 2									
Menu	1	2	3	4	5	6	7	8	**Total**
Energy (kcal)	1,191.02	1,207.66	1,140.16	1,520.63	1,309.96	1,027.47	1,201.65	1,061.06	
Protein (g)	47.96	46.50	51.40	102.20	55.02	38.01	51.11	49.09	
Fat (g)	27.67	26.36	22.69	28.42	17.32	9.77	9.42	7.46	
Carbohydrate (g)	205.18	207.77	196.07	220.27	238.26	203.34	227.13	202.69	
Fiber (g)	10.69	24.79	10.48	24.52	17.76	5.20	19.77	5.20	
Fitness 1	0	0	0	1	1	1	1	1	5
Fitness 2	92.65	157.47	116.14	1,000	1,000	1,000	1,000	1,000	5,366.26

The cases in Table 4 were tested using the DE/rand/1 and DE/best/1 mutation functions with population sizes of 20 and 30 [30], [31]. The maximum iteration variations used were 1,000, 1,500, and 2,000. Each test was conducted 20 times, and the average results are presented in Tables 7 to 10. The average test results from Tables 7 and 8 are shown in Figure 2, while the results from Tables 9 and 10 are displayed in Figure 3.

Table 7. Testing on Population 20 with DE/rand/1 Mutation Function

Iteration	Menu				Time (seconds)			
	Case 1	Case 2	Case 3	Case 4	Case 1	Case 2	Case 3	Case 4
1,000	2.05	5.15	5.85	15.20	0.61	2.16	6.91	7.02
1,500	2.10	4.90	5.70	16.40	0.80	3.07	16.65	11.18
2,000	1.70	4.40	5.00	10.25	0.80	3.60	17.53	18.84

Table 8. Testing on Population 30 with DE/rand/1 Mutation Function

Iteration	Menu				Time (seconds)			
	Case 1	Case 2	Case 3	Case 4	Case 1	Case 2	Case 3	Case 4
1,000	2.15	4.85	8.70	17.20	0.83	3.08	7.21	10.97
1,500	2.25	3.75	7.50	18.00	1.53	4.96	9.23	18.17
2,000	2.25	5.20	6.70	17.65	2.06	5.82	10.61	22.57

Table 9. Testing on Population 20 with DE/best/1 Mutation Function

Iteration	Menu				Time (seconds)			
	Case 1	Case 2	Case 3	Case 4	Case 1	Case 2	Case 3	Case 4
1,000	0.45	0.60	0.35	1.90	0.50	1.94	3.34	13.35
1,500	0.60	0.70	1.25	3.90	0.42	3.10	5.20	19.66
2,000	0.60	1.35	0.35	3.50	0.85	4.47	7.47	24.96

Table 10. Testing on Population 30 with DE/best/1 Mutation Function

Iteration	Menu				Time (seconds)			
	Case 1	Case 2	Case 3	Case 4	Case 1	Case 2	Case 3	Case 4
1,000	0.50	0.60	1.10	2.00	1.02	3.25	5.09	17.17
1,500	0.60	1.05	0.35	3.35	1.19	4.24	8.80	27.45
2,000	0.50	1.30	0.75	2.35	1.40	4.43	9.38	36.18

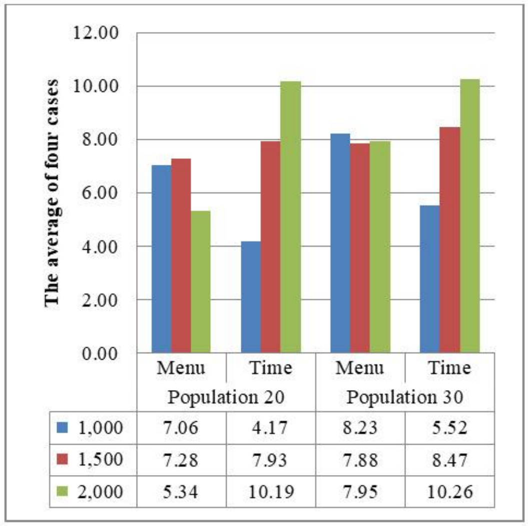

Figure 2. Average Test Results from DE/rand/1 Mutation Function

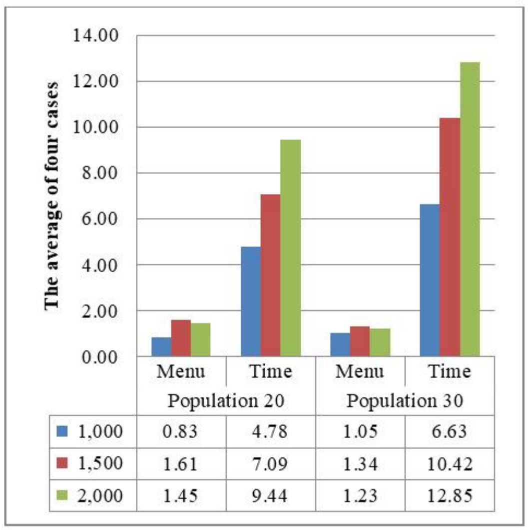

Figure 3. Average Test Results from DE/best/1 Mutation Function

In Figures 2 and 3, it can be observed that the DE/rand/1 mutation function produces the best results. It indicates that the DE/rand/1 mutation function has a superior exploration capability compared to the DE/best/1 mutation function. The optimal parameters for the DE/rand/1 mutation function are a population of 30 and a maximum of 1,000 iterations, which yield the highest number of menus and competitive computation time.

The final test analyses the distribution of food ingredient occurrences using the DE/rand/1 mutation function, with a population of 30 and a maximum of 1,000 iterations. The test was conducted on a composition of 10 food ingredients in each category: staple foods, protein sources, and vegetables. Figure 4 and Figure 5 show that staple foods and vegetables have a more uniform distribution, indicating that each ingredient has an equal chance of appearing in every menu. Although protein sources are more varied, almost all types can still be included in the menu. It indicates that the menus generated by the system are sufficiently diverse.

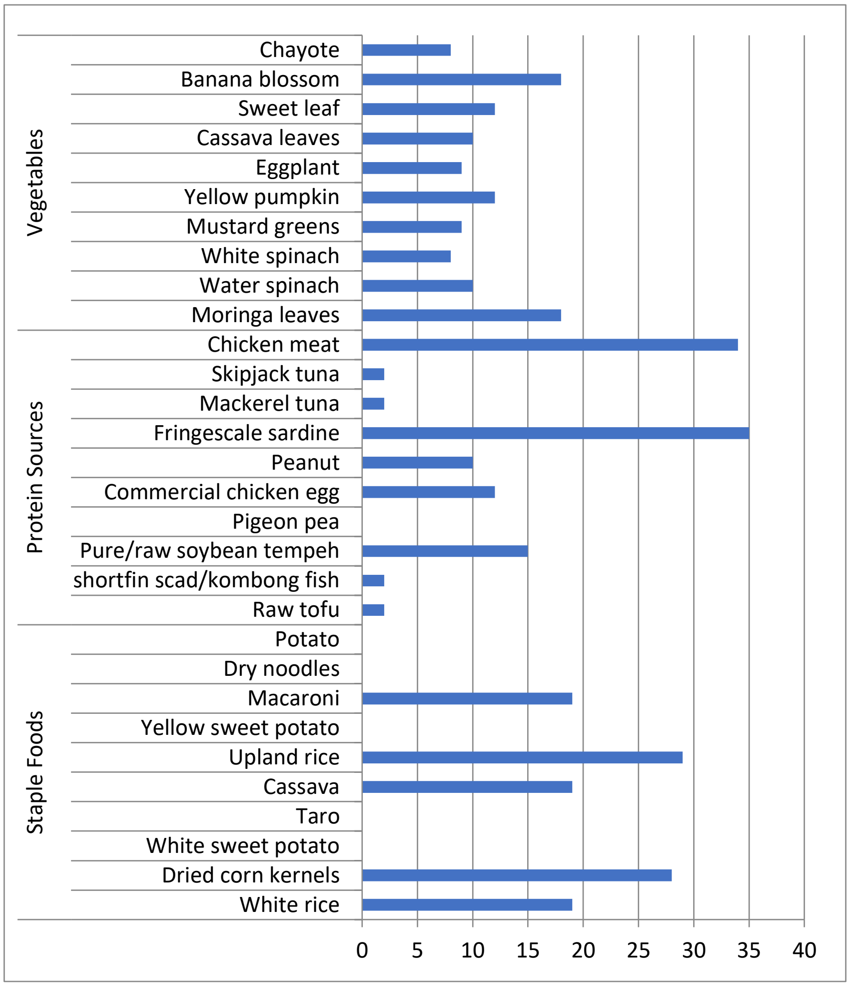

Figure 4. Distribution of 30 food ingredients, generating 114 menus

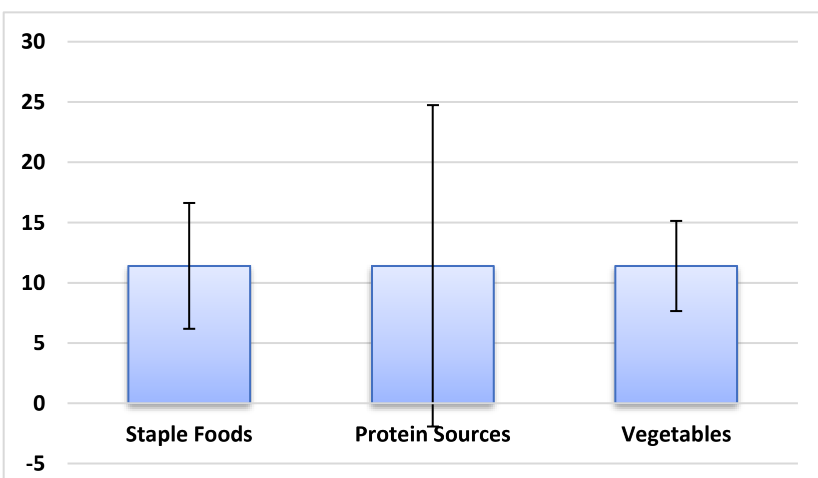

Figure 5. The mean and standard deviation of Figure 4.

4. CONCLUSION

The Differential Evolution (DE) algorithm can be applied to solve multi-objective optimisation problems, such as menu planning. Proper food portions and nutrition from an early age have the potential to reduce key risk factors affecting children's growth and development. Our proposed approach enables efficient menu variation based on the availability of ingredients owned by parents while considering children's portion sizes and nutritional needs. This study also demonstrates that the DE/rand/1 mutation function outperforms DE/best/1. The DE/rand/1 mutation function generates more feasible menus while offering faster execution time, with optimal parameters set at a population size of 30 and a maximum of 1,000 iterations. Additionally, ingredient distribution using the DE/rand/1 mutation function with optimal parameters results in a more diverse menu. Future research recommendations include incorporating fruit as an additional food ingredient and considering more essential nutrients, such as minerals and vitamins.

ACKNOWLEDGEMENT

To ensure transparency and reproducibility, the data used in this research is an open dataset available to the public, as outlined in the Method section. Researchers can verify and build upon results because of transparency, enabling a collaborative scientific environment.

AUTHOR CONTRIBUTIONS

Conceptualization, A.F. Y.T.P. and J.R.M.L.; methodology, A.F.; software, Y.T.P. and S.A.D.; validation, A.S.K. and Y.T.P.; formal analysis, A.F. and Y.T.P.; investigation, A.F. and Y.T.P.; resources, A.F. and S.A.D.; data curation, J.R.M.L. and A.F.; writing—original draft preparation, A.S.K., C.E.A.P., B.P. and A.F.; writing—review and editing, C.E.A.P., A.F., Y.T.P., A.S.K., A.Y.M. and J.R.M.L.; visualization, A.S.K. and A.Y.M.; supervision, S.A.D. and B.P.; project administration, A.F.; funding acquisition, A.F.. All authors have read and agreed to the published version of the manuscript.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest.

REFERENCES

[1] E.C. Sugiarto, Pembangunan Sumber Daya Manusia (SDM) Menuju Indonesia Unggul, Kementerian Sekretariat Negara Republik Indonesia, Accessed: February 06, 2025.

https://www.setneg.go.id/baca/index/pembangunan_sumber_daya_manusia_sdm_menuju_indonesia_unggul.

[2] K.E. Lestari, A. Warmi, S. Winarni, et al. Revealing the Hidden Pattern Of Under-Five Malnutrition Prevalence Distribution in West Java-Indonesia from Canonical Correspondence Analysis and Predictive Clustering Perspective, Commun. Math. Biol. Neurosci. 2024 (2024), 132. https://doi.org/10.28919/cmbn/8915.

[3] AO, IFAD, UNICEF, WFP, WHO, The State of Food Security and Nutrition in the World 2022, FAO, 2022. https://doi.org/10.4060/cc0639en.

[4] UNICEF-Indonesia, Selain Stunting, Wasting Juga Salah Satu Bentuk Masalah Gizi Anak yang Perlu Diwaspadai, UNICEF, Accessed: February 06, 2025. https://www.unicef.org/indonesia/id/gizi/artikel/stunting-wasting-sama-atau-beda.

[5] UNICEF dan Kementerian Kesehatan Republik Indonesia, Menuju Masa Depan Indonesia Bebas Masalah Kekurangan Gizi, 2023. https://www.unicef.org/indonesia/media/20441/file/Menuju%20Masa%20Depan%20Indonesia%20Bebas%20Masalah%20Kekurangan%20Gizi.pdf.

[6] Badan Pusat Statistik (BPS), Jumlah dan Persentase Balita Wasting Menurut Kabupaten/Kota, 2021-2023, Badan Pusat Statistik (BPS). Accessed: February 06, 2025. https://ntt.bps.go.id/id/statistics-table/2/MTU3MiMy/jumlah-dan-persentase-balita-wasting-menurut-kabupaten-kota.html.

[7] D. Sudigyo, A.A. Hidayat, R. Nirwantono, R. Rahutomo, J.P. Trinugroho, B. Pardamean, Literature Study of Stunting Supplementation in Indonesian Utilizing Text Mining Approach, Procedia Computer Sci. 216 (2023), 722–729. https://doi.org/10.1016/j.procs.2022.12.189.

[8] B. Pardamean, R. Rahutomo, D. Sudigyo, et al. Evaluation of Childhood Stunting Reduction Treatments in Indonesia, Preprint (2023). https://doi.org/10.21203/rs.3.rs-2987821/v1.

[9] R. Rahutomo, G.N. Elwirehardja, M. Isnan, et al. Machine Learning Implementations in Childhood Stunting Research: A Systematic Literature Review, in: 2023 International Conference on Information Management and Technology (ICIMTech), IEEE, Malang, Indonesia, 2023: pp. 229–234. https://doi.org/10.1109/icimtech59029.2023.10277881.

[10] R.E. Caraka, K. Supardi, P.A. Kaban, et al. Understanding Pediatric Health Trends in Papua: Insights From SUSENAS, RISKESDAS, Remote Sensing, and Its Relevance to Prabowo and Gibran’s Free Lunch and Milk Program, IEEE Access 12 (2024), 51536–51555. https://doi.org/10.1109/access.2024.3380018.

[11] UNICEF_Indonesia, Wasting (Gizi Kurang dan Gizi Buruk) dan Dampaknya pada Anak, UNICEF. Accessed: February 06, 2025. https://www.unicef.org/indonesia/id/gizi/artikel/dampak-wasting-pada-anak.

[12] Badan Pusat Statistik (BPS), Persentase Penduduk Berumur 10 Tahun Ke Atas Menurut Jenis Kelamin dan Ijazah Tertinggi (Persen), 2022-2023, Badan Pusat Statistik (BPS). Accessed: Feb. 06, 2025.

https://ntt.bps.go.id/id/statistics-table/2/MTI3IzI=/persentase-penduduk-berumur-10-tahun-ke-atas-menurut-jenis-kelamin-dan-ijazah-tertinggi.html.

[13] B.K. Seljak, Computer-Based Dietary Menu Planning, J. Food Compos. Anal. 22 (2009), 414–420. https://doi.org/10.1016/j.jfca.2009.02.006.

[14] P. Bello, P. Gallardo, L. Pradenas, J.A. Ferland, V. Parada, Best Compromise Nutritional Menus for Childhood Obesity, PLOS ONE 15 (2020), e0216516. https://doi.org/10.1371/journal.pone.0216516.

[15] C. Türkmenoğlu, A.Ş.E. Uyar, B. Kiraz, Recommending Healthy Meal Plans by Optimising Nature-Inspired Many-Objective Diet Problem, Health Inform. J. 27 (2021), 1–10. https://doi.org/10.1177/1460458220976719.

[16] R.P.C. Moreira, E. Wanner, F.V.C. Martins, J.F.M. Sarubbi, An Evolutionary Mono-Objective Approach for Solving the Menu Planning Problem, in: 2018 IEEE Congress on Evolutionary Computation (CEC), IEEE, Rio de Janeiro, 2018: pp. 1–8. https://doi.org/10.1109/cec.2018.8477888.

[17] J. Sun, X. Liu, T. Back, Z. Xu, Learning Adaptive Differential Evolution Algorithm From Optimization Experiences by Policy Gradient, IEEE Trans. Evol. Comput. 25 (2021), 666–680. https://doi.org/10.1109/tevc.2021.3060811.

[18] B. Hegerty, C. Hung, K. Kasprak, A Comparative Study on Differential Evolution and Genetic Algorithms for Some Combinatorial Problems, in: Proceedings of 8th Mexican International Conference on Artificial Intelligence, 2009, pp 9–13.

[19] A. Fanggidae, M. Boru, Analisis Algoritma DE , ABC , PSO dalam Penentuan Parameter Karakteristik Input-Output Pembangkit Termal, in: Prosiding Seminar Nasional Ilmu Komputer (SNIK) 2017, Semarang: Jurusan Ilmu Komputer FMIPA UNNES, 2017, pp. 71–78.

[20] N. Lukman, M. Irfan, A. Nugraha, J. Jumadi, Comparison between Genetic Algorithm with Differential Evolution in Study Scheduling, IOP Conf. Ser.: Mater. Sci. Eng. 1098 (2021), 032082. https://doi.org/10.1088/1757-899x/1098/3/032082.

[21] F.S. Hsieh, Development and Comparison of Ten Differential-Evolution and Particle Swarm-Optimization Based Algorithms for Discount-Guaranteed Ridesharing Systems, Appl. Sci. 12 (2022), 9544. https://doi.org/10.3390/app12199544.

[22] Kementerian Kesehatan Republik Indonesia, Tabel Komposisi Pangan Indonesia 2017, Jakarta: Kementerian Kesehatan RI, 2018.

[23] Kementerian Kesehatan Republik Indonesia, Peraturan Menteri Kesehatan Republik Indonesia Nomor 2 Tahun 2020 Tentang Standar Antropometri Anak, Kementerian Kesehatan Republik Indonesia, 2020, pp. 1–78.

[24] S. Bintanah, H.S. Kusuma, Y.N.S. Ulvie, et al. Perhitungan Kebutuhan Gizi Individu, Semarang: NextBook,

2018.

[25] B.V. Babu, S.A. Munawar, Differential Evolution Strategies for Optimal Design of Shell-and-Tube Heat Exchangers, Chem. Eng. Sci. 62 (2007), 3720–3739. https://doi.org/10.1016/j.ces.2007.03.039.

[26] Y. Yang, Y. Chen, Y. Wang, et al. Modelling a Combined Method Based on ANFIS and Neural Network Improved by DE Algorithm: A Case Study for Short-Term Electricity Demand Forecasting, Appl. Soft Comput. 49 (2016), 663–675. https://doi.org/10.1016/j.asoc.2016.07.053.

[27] X.S. Yang, Nature-Inspired Optimization Algorithms, Academic Press, 2020.

[28] M.F. Ahmad, N.A.M. Isa, W.H. Lim, et al. Differential Evolution: A Recent Review Based on State-of-the-Art Works, Alexandria Eng. J. 61 (2022), 3831–3872. https://doi.org/10.1016/j.aej.2021.09.013.

[29] E. Mezura-Montes, J. Velázquez-Reyes, C.A. Coello Coello, A Comparative Study of Differential Evolution Variants for Global Optimization, in: Proceedings of the 8th Annual Conference on Genetic and Evolutionary Computation, ACM, Seattle Washington USA, 2006: pp. 485–492. https://doi.org/10.1145/1143997.1144086.

[30] A. Fanggidae, M.I.C. Prasetyo, Y.T. Polly, et al. New Approach of Self-Adaptive Simulated Binary Crossover-Elitism in Genetic Algorithms for Numerical Function Optimization, Int. J. Intell. Syst. Appl. Eng. 12 (2024), 174–183.

[31] Y.T. Polly, S. Hartati, Suprapto, et al. A Novel Approach to Multi-Layer-Perceptron Training Using Quadratic Interpolation Flower Pollination Neural Network on Non-Binary Datasets, Int. J. Adv. Computer Sci. Appl. 14 (2023), 497-504. https://doi.org/10.14569/ijacsa.2023.0140653.