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A HYBRID PARTICLE SWARM OPTIMIZATION TO SOLVE DIETARY MENU PLANNING

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ABSTRACT: Several metaheuristic approaches have been devised to deal with the tedious and cumbersome nature of dietary menu planning. In particular, Particle Swarm Optimization (PSO) has been used due to its efficiency and simplicity.However, even classical PSO has been shown to output suboptimalsolutions. In this study, fuzzy evaluation and genetic operators were integrated into PSO to improvedecision-making capabilities and increase the chances of choosing better quality solutions. The results of the study show that the integration of fuzzy evaluation and genetic operators into the classical PSO has addressed itslimitation of coming up with suboptimal solutions. This finds particular importance in decision-makingtowards better quality dietary meal planning.

KEYWORDS:— *Particle Swarm Optimization; Genetic Operators; Dietary Menu Planning; Fuzzy Evaluation*

1.0 INTRODUCTION

Dietary menu planning is scheduling of meals to assess individual nutritional needs for an entire day. The aim of dietary menu planning is to attain dietary intakes that are adequate but not excessive [1]. Accordingly, the menu planning is an example of planning research, which is considered as a complicated task in finding a combination of a different menu that satisfies several goals and constraints [1]–[3]. It is considered as an NP-hard, and multimodal problem because solving this problem is tedious and cumbersome [4]. Various optimization approaches have been applied to solve dietary menu planning problems, including linear programming, integer programming, mixed-integer linear programming, goal programming and multistage multiple-choice programming algorithm [1], [5]. However, metaheuristic approaches and optimization became the currently popular approach in solving the menu planning problem. Considering that malnutrition is a prevalent health problem that relates to different

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forms of illnesses, dietary menu planning will help address the problem of improper diet [6]. The common misconception on malnutrition is on its form, and many people usually refer it to undernutrition only. But its form ranges from severe undernutrition to overweight and obesity and resulting in diet-related diseases. Mediocrities in diet and health care environment and behaviors are some of the risk factors of malnutrition [7]. As indicated in the, 2.01 billion adults from ages 18 and above are overweight and of which 678 million are obese [8]. Overweight and obesity are defined as an unnecessary buildup of fats in the body that may cause health problems [8] that may lead to different diseases if untreated [9].Also, it was estimated that 10 percent of the population were suffering from chronic undernourishment in 2016 [10]. Though, evidence in the Philippines suggests that the prevalence of overweight/obesity surpasses the number of undernutrition by one-third of the population among adults aged 19 and above [11]. Health problems such as overweight and obesity and non-communicable diseases can be addressed if people will adhere to proper dietary objectives [12].

In generating a diet menu, many suitable approaches can be applied to produce it depending on the individual's nutritional facts. Automated planning technology has been an interesting choice of study for many researchers making it more useful in many fields that range from medicine to space exploration [13]. Furthermore, this study will apply Particle Swarm Optimization (PSO) to solve the dietary menu problems in pertinent to the Philippines dietary reference intakes since most Filipino children and adolescents lack proper nutrient intakes, and most adults age 25 and above shows high level of saturated fat, sodium, and sugar-sweetened beverage intakes that results to non-communicable diseases [14]. In this study, the basis for formulating the solutions is the dietary intake guideline, which was released in 2015 by the Philippines Food and Nutrition Research Institute. In the guideline, the acceptable macronutrient distribution range, recommended intakes for macronutrients, vitamins, and minerals are specified together with the tolerable upper intake levels or upper limits per day.

2.0 LITERATURE REVIEW

A metaheuristic algorithm is an iterative searching process in finding an efficient solution to different optimization problems within a reasonable computational cost [15], [16], [17]. These approaches are classified as single-solution based methods that manipulate and improve a single solution during the iteration and the population-based approach that is a nature-inspired algorithm that maintains and improves multiple solutions during the searching process [18]–[20], [21]. Accordingly, the population-based methods perform better compared to the single-solution approaches [22]. Moreover, the population-based method can handle more complex optimization problems [23]. The population-based techniques are the following, but not limited to: Genetic Algorithm, Evolutionary Algorithm, Differential Evolution, Particle Swarm Optimization, Ant Colony, Bee Colony, Bacterial Foraging Optimization, Artificial

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Immune System and many others [24].From the mentioned metaheuristic approaches, the Particle Swarm Optimization (PSO) was chosen to solve the dietary menu problem that meets the Philippine dietary reference intakes. Hence, PSO had been widely used and been successful in solving numerous optimization problems because it is simpler to implement and has a minimal parameter to tuned [25]–[27]. PSO is a robust method that simulates the swarming theory, and it is suited to solve various optimization problems due to its efficiency and effectivity as compared to other evolutionary algorithms [19], [28], [29]. However, particles in PSO tend to lose their diversity, which results in early convergence and ends up to a suboptimal solution [30]–[32]. This present study supplements the existing knowledge in computing by improving the performance of PSO by integrating fuzzy evaluation and genetic operators to solve the dietary planning problem. Also, the study could give a simple environment where people can plan and identify appropriate menus and dishes that satisfy the energy, macronutrients, and micronutrients requirements and ensures equal distribution of proper food group proportion in every meal.

3.0 MATERIALS AND METHODS

3.1 Hybrid Particle Swarm Optimization

The PSO algorithm is a meta-heuristic method consist of a population of particles that are initialized randomly. Each particle is specified by a position that represents a solution in the form of a vector. The particle's position is updated in every generation, as shown in equations (1) and (2).

$$V_{id}{}^{(t+1)} = \acute{\omega}\, V_{id}{}^{(t)} + c_1 . rand_1 . \left(P_{pd} - X_{id}\right) + c_2 . rand_2 . (P_{gd} - X_{id}) \quad (1)$$

$$X_{id}{}^{(t+1)} = X^{(t)}{}_{id} + V_{id}{}^{(t+1)} \quad (2)$$

wherec_1 is the personal acceleration coefficient, c_2 is the social acceleration coefficient, and ώ is the inertia coefficient. A particle acquires a new position guided by the velocity $V_{id}{}^{(t)}$, and $rand_1$ and $rand_2$ are real random numbers that are uniformly distributed between 0 and the size of the decision variable. The current position is denoted by $X^{(t)}{}_{id}$, $V_{id}{}^{(t+1)}$ is the updated velocity, $X_{id}{}^{(t+1)}$is the updated position and X_{id} is the current particle position. In every generation, a local best P_{pd}, and a global best P_{gd} are identified using the fitness of current particle in the population. Further, in this work, the particle swarm optimization is integrated with genetic operators and fuzzy evaluation, as shown in Figure 1.

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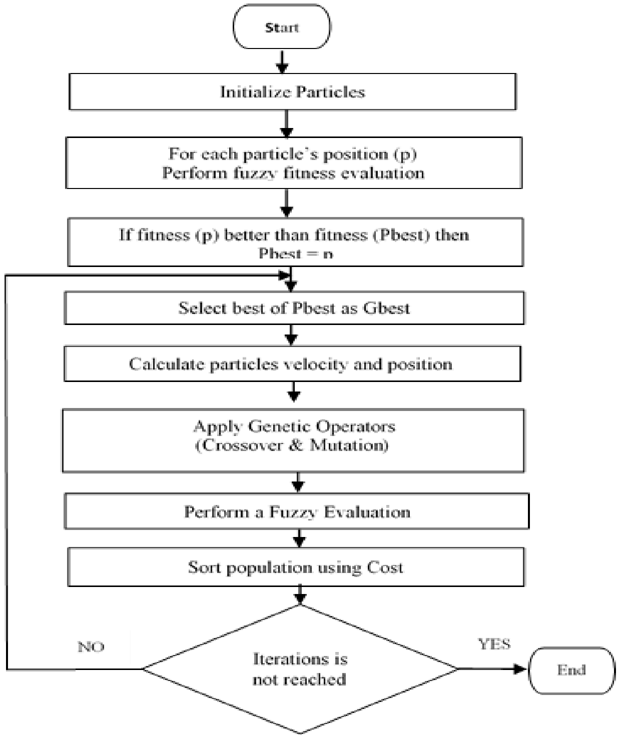

Figure 1: The Proposed Hybrid Particle Swarm Optimization

3.2 Fuzzy Evaluation

Every individual in the swarm was evaluated to determine the meal plan quality as to Very Healthy, Healthy, Fair Healthy, Unhealthy, and Very Unhealthy, as shown in Table 1. The meal plan quality is determined by the food group proportion (FGP) penalty cost. From four identified food groups, namely: Fruits, Go, Grow, and Vegetables, two criteria were considered: the average penalty and the highest penalty.

Table 1: Food Group Distribution Range of the Output

Distribution Range	**Scale**	**Indicator**
0.0, 0.1062	1	Very Unhealthy
0.1061, 0.25	2	Unhealthy
0.26, 0.50	3	Fair Healthy
0.51, 0.75	4	Healthy
0.76, 1	5	Very Healthy

The union of the two fuzzy sets for penalties (membership function average penalty and membership function the highest penalty, shown in Figures 2 and 3, respectively) defines the quality of the meal plan.

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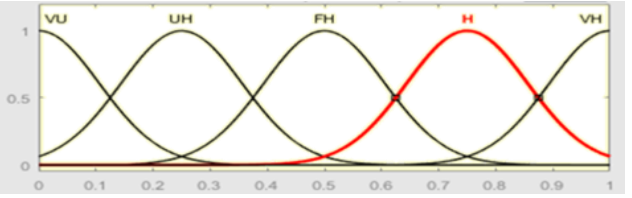

Figure 2: Membership Functions of the Average and Highest Penalty

The average penalty and highest penalty were represented by five linguistic terms namely; Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH).

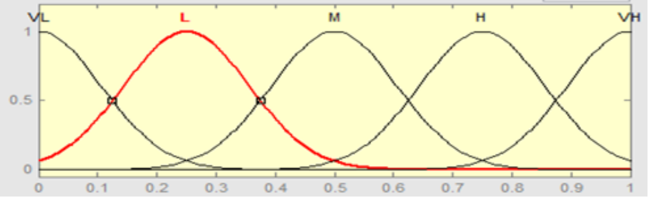

Figure 3: Membership Function of the Quality

The average penalty and highest penalty were represented by five linguistic terms namely; Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH). On the other hand, the quality is represented by five terms, namely; Very Unhealthy (VU), Unhealthy (UH), Fair Healthy (FH), Healthy (H), and Very Healthy (VH) as shown in Table 2.

Table 2: Example Fuzzy Rules for Fuzzy Evaluation Function

Rule	**Average Penalty**	**Highest Penalty**	**Output**	**Rule**	**Average Penalty**	**Highest Penalty**	**Output**
1	VL	VL	Very Healthy	14	Medium	High	Unhealthy
2	VL	Low	Healthy	15	Medium	VH	Unhealthy
3	VL	Medium	Fair Healthy	16	High	VL	Unhealthy
4	VL	High	Unhealthy	17	High	Low	Unhealthy
5	VL	VH	Very Unhealthy	18	High	Medium	Unhealthy
6	Low	VL	Very Healthy	19	High	High	Unhealthy

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7	Low	Low	Healthy	20	High	VH	Very Unhealthy
8	Low	Medium	Fair Healthy	21	VH	VL	Very Unhealthy
9	Low	High	Unhealthy	22	VH	Low	Very Unhealthy
10	Low	VH	Very Unhealthy	23	VH	Medium	Unhealthy
11	Medium	VL	Fair Healthy	24	VH	High	Very Unhealthy
12	Medium	Low	Fair Healthy	25	VH	VH	Very Unhealthy
13	Medium	Medium	Fair Healthy				

Thus, the proposed method may produce particles having the same cost but differs in quality or having a varied food group distribution, or it may produce a particle having minimal cost but has a low quality compared to particles with a higher cost, but with higher quality.

3.3 Genetic Operators

Crossover and mutation were integrated towards the end of the run to evolve better at the start of every iteration. A single-point crossover was applied to yield a new particle, called a child, which contains a better gene than the two parents. The particles are then mutated using a single-point mutation.Tournament selection was used in the selection of parent chromosomes that were used for the crossover operator.

3.4 Constraints

This dietary planning problem involves consideration of various kinds of constraints that must be satisfied. These constraints were made through a mathematical model, in such a way that the optimal solutions should be close to the Daily Recommended Energy Intake, Acceptable Macronutrient Distribution Range, and Daily Recommended Nutritional Intake for vitamins and minerals without going over the Daily Tolerable Nutrient Intake provided by DOST-FNRI through the Philippine Dietary Reference Intake. These constraints are:

3.4.1 Energy Constraint

There is a need to satisfy a person's level of energy intake. Thus, it must not exceed the upperand lower limit of the total energy requirement. In the equation below, Aej is the quantity of energyin every serving of the food item j, Yj is the quantity of food item j, while E denotes the total energy allowance for a day of an individual, and n is the number of foods per meal.

$$\sum_{j \in J} A_j \leq E, \quad \sum_{j \in J} A_j \geq E \qquad (3)$$

3.4.2 Macronutrients

In macronutrients, there are adequate intake values based on the recommended energy andnutrient intakes. Thus, daily intakes of macronutrients should be within the range based on the Acceptable
Macronutrient Distribution Range (AMDR).

$$\sum_{j \in J} A_{pj}.4 \geq 0.1E, \quad \sum_{j \in J} A_{pj}.4 \leq 0.15E \qquad (4)$$

$$\sum_{j \in J} A_{fj}.9 \geq 0.15E, \quad \sum_{j \in J} A_{fj}.9 \leq 0.30E \qquad (5)$$

$$\sum_{j \in J} A_{cj}.4 \geq 0.55E, \quad \sum_{j \in J} A_{cj}.4 \leq 0.75E \qquad (6)$$

whereApj, Afj, Acj denote the number of proteins, fats and carbohydrates in every serving of food item j, and n is the number of foods in the meal. Since quantities of macronutrients are expressed in grams, the need to convert it into calories is required (e.g., 4 for protein and carbohydrates and 9 for fats), while E is the recommended calorie requirement value for a day.

3.4.3 Micronutrients

On the other hand, the micronutrients should be according to the Recommended Nutrient Intake (RENI) per day, and it must not exceed the Tolerable Upper Intake Levels or Upper Limits (UL) per day which is considered adequate for the maintenance of health and well-being of a person. Eight nutrients were considered, and this is based on the Philippine Dietary Reference Intake (PDRI) such as Calcium, Phosphorous, Iron, Vitamin A, Vitamin B1 or Thiamin, Vitamin B2 or Riboflavin, Vitamin B3 or Niacin, and Vitamin C.

$$\sum_{j \in J} i_j \geq RENI \qquad (7)$$

$$\sum_{j \in J} i_j \leq UL \qquad (8)$$

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whereAij means the quantity of nutrient i in one unit of the food item j, for all item i = 1..n, and for all j = 1,..m.

3.4.4 Food Group Proportion

Every individual adult must consume a variety of foods. Thus, food groups are well represented in every meal by a quantity that is equivalent to its portion size (e.g., ½ of the plate is for Glow foods with 1/3 for fruits and 1/6 for vegetables, 1/3 for Grow foods and 1/6 for Go foods). These constraints can be expressed as:

$$\sum_{j \in \mathrm{J}} A_{Goj} = .33E \tag{9}$$

$$\sum_{j \in \mathrm{J}} A_{Grj} = .17E \tag{10}$$

$$\sum_{j \in \mathrm{J}} A_{Vj} = .33E \tag{11}$$

$$\sum_{j \in \mathrm{J}} A_{Frj} = .17E \tag{12}$$

where A_{Goj}, A_{Grj}, A_{Vj}, and A_{Frj} denotes the calorie content of the food item (dish) $j \in$ J that belongs to food groups.

The foods are categorized into Go foods, Glow foods (fruits and vegetables) and Grow foods. This constraint ensures that every food type is present in every meal. Therefore, each food group must have three dishes on the menu. Hence three meals (breakfast, lunch, and dinner) are required for a day. The constraint can be presented as:

$$\sum_{j \in \mathrm{J}} GoFoods(\mathrm{j}) = 3, \tag{13}$$

$$\sum_{j \in \mathrm{J}} GrowFoods(\mathrm{j}) = 3, \tag{14}$$

$$\sum_{j \in \mathrm{J}} Vegetables(\mathrm{j}) = 3, \tag{15}$$

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$$\sum_{j \in J} Fruits(\mathrm{j}) = 3, \qquad (16)$$

where $GoFoods(\mathrm{j}) \in \{0,1\}$, $GrowFoods(\mathrm{j}) \in \{0,1\}$, $Vegetables(\mathrm{j}) \in \{0,1\}$, and $Fruits(\mathrm{j}) \in \{0,1\}$. The functions $oFoods(\mathrm{j})$, $GrowFoods(\mathrm{j})$, $Vegetables(\mathrm{j})$, and $Fruits(\mathrm{j})$ will return 1 if the food item j belongs to the group of food; otherwise, it will return 0.

3.4.5 Other Constraints

There are also other specific recommendations that must be maintained at a certain level such as dietary fiber, sodium, and potassium. The amount of sodium intake should be limited to only less than 2 grams, where $s_j$is the amount of sodium, s, in every serving of food item, j; thus, equation 17 shows.

$$\sum_{j \in J} s_j \leq 2. \qquad (17)$$

Since the amount of potassium must be increased to 3,510 mg, the formula in Equation 18 is used where $t_j$is the amount of potassium t in every serving of food item j.

$$\sum_{j \in J} t_j \geq 3510. \qquad (18)$$

On the other hand, a daily intake of 25 grams of dietary fiber is highly recommended for adults, and this can be expressed as:

$$\sum_{j \in J} b_j \geq 25. \qquad (19)$$

The list of macronutrients and micronutrients constraints are based on World Health Organization Acceptable Macronutrient Distribution Range (AMDR) and Recommended Nutrient Intake (RNI). Shown in Table 3 and Table 4 below are the recommended range of intakes for macronutrients and micronutrients, respectively.

Table3: Macronutrients Distribution Range

Age Group	**Range (% of Energy)**		
Adults (19-59 years old)	Protein	Fats	Carb
	10-15%	15-30%	55-75%

Table4: Micronutrients Recommended Nutrient Intakes and Upper Limits per day

Micronutrients	**Male**	**Female**

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	RNI	UL	RNI	UL
Calcium (mg)	750	3000	750	3000
Phosphorous (mg)	700	4000	700	4000
Iron (mg)	12	45	28	45
Vitamin A (μg RE)	700	3000	600	3000
Thiamin (Vitamin B1) (mg)	1.2	-	1.1	-
Riboflavin (Vitamin B2) (mg)	1.3	-	1.1	-
Niacin (Vitamin B3) (mg NE)	16	35	14	35
Vitamin C	70	1000	60	1000
Dietary Fiber	20	25	20	25
Sodium	≤ 2g			
Potassium	≥ 3510mg			

3.4.6 Menu Quality

The solution is given an additional cost based on the quality of the dishes on the menu, as shown in equation (20):

$$\text{QualityCost} = \text{FuzzyEvaluation}(J), \qquad (20)$$

where J is the set of dishes, FuzzyEvaluation(J)∈{1,2,3,4,5}, based on the values and scales presented in Table 1.

3.4.7 Objective Function

This study aimed to find a diet plan with minimum penalty cost by satisfying the required constraints. Shown below is the equation for the objective function:

$$Penalty = \sum_{J \in \mathrm{J}} \sum_{k \in K} W_{jk}\,, \qquad (21)$$

whereJ is the set of dishes (food items), K is the set of constraints, and W is the penalty cost for every violated constraint k for dish j. Furthermore, every constraint violation is set to have a penalty of 1 except for the quality constraint, and food group proportion and energy constraint, where every energy (kcal) not met or goes over the limit is equivalent to 1 penalty.

3.4.8 Food Database

The datasets were gathered from published books and websites of the Food and Nutrition Research Institute and Philippine National Nutrition Council, and other

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Filipino food menu or recipes found from reliable internet websites. The dataset comprised of 800 food items with corresponding nutritional value, serving size, and food group type, an example is shown in Table 5.

Table 5: Sample Food Item Information Stored in the Food Database

Dish Name:	**Beef Pochero**		
Key	Value	Key	Value
Calories	91	Riboflavin (mg)	0.11
Protein	4	Niacin (mg NE)	2
Fats	2	Vitamin C	54
Carbo	17	Sodium	0.51
Calcium (mg)	110	Potassium	0
Phosphorus (mg)	92	Fiber	8
Iron (mg)	1.7	Serving Size	107 grams
Vitamin A (μg RE)	580	Cost	40.00 Pesos
Thiamin (mg)	0.18	Food Group	Grow Foods

4.0 RESULTS

The proposed methods are tested using Matlab 2017a, and solutions from classical PSO and PSO with Genetic Operators were compared. Also, both approaches were using fuzzy evaluation to enable the algorithms to find a solution having equal distribution on food group proportions since the constraint is hard to achieve. Table 6 shows the PSO with genetic operators produces a best-fit solution with a fitness or cost value of 33.40 and 40.40 using a swarm size of 300 within 1000 iterations as compared to 71.19 and 121.11 generated by classical PSO for both daily and weekly meal plan. Furthermore, similar results were also observed using a swarm size of 200 within 750 iterations and a swarm size of 150 within 500 repetitions. The results clearly show that genetic operators can help the PSO to explore the search space better. Shown in Table 7 and Table 8 is the quality of the solution produced by the classical PSO and the Hybrid PSO. As can be seen, the Hybrid PSO satisfies more constraints compared to the conventional PSO, especially on the food group proportion and required number of types of foods. The generated menus complied the requirements set by Philippine Dietary Reference Intake through Acceptable Macronutrient Distribution Range (AMDR), Recommended Energy and Nutrient Intakes (RENI) and PinggangPinoy. Also, it was observed that some of the goals were not achieved.

Table6.:Comparison of Best Solution Produce by the Classical PSO and Hybrid PSO

Methods	**Daily Meal Plan**			**Weekly Meal Plan**		
	PSO	**Hybrid PSO**	*	**PSO**	**Hybrid PSO**	*
Average Cost	71.19	33.40	53%	121.11	40.40	66%

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Iterations	1000	1000		1000	1000	
Swarm Size	300	300		300	300	
Average Cost	71.71	34.04	52%	139.54	51.04	63%
Iterations	750	750		750	750	
Swarm Size	200	200		200	200	
Average Cost	82.38	39.63	57%	158.77	52.74	66%
Iterations	500	500		500	500	
Swarm Size	150	150		150	150	

Note: * denotes the improvement rate from PSO to Hybrid PSO

Table 7: Analysis of the Best Solution Generated by the PSO and Hybrid PSO using 1000 Generations

	AMDR & RENI	Classical PSO		Hybrid PSO	
		Acquired Nutrients	Goal Achieved	Acquired Nutrients	Goal Achieved
Energy (kcal)	1450-1550	1492	Yes	1500	Yes
Protein	10-15%	17%	No	15%	Yes
Fats	15-30%	23%	Yes	25%	Yes
Carbohydrates	55-75%	63%	Yes	62%	Yes
Calcium	750-3000	849	Yes	700	No
Phosphorous	700-4000	1270	Yes	1166	Yes
Iron	28-45	35	Yes	28	Yes
Vitamin A	600-3000	8520	No	5129	No
Thiamin	1.1-	2	Yes	2	Yes
Riboflavin	1.1-	2.5	Yes	3	Yes
Niacin	14-35	42	No	35	Yes
Vitamin C	60-1000	487	Yes	301	Yes
Sodium	<2 grams	3	No	3	No
Potassium	>3510	3717	Yes	3000	No
Fiber	20-25	32	No	27	No

However, if a ±25% error rate is applied as suggested by a dietitian, most of the vitamins and minerals contained in the menu are within the acceptable ranges. Moreover, both algorithms generate a menu that is close to reaching the exact food group proportion percentage. The hybrid approach satisfies only the fruits, while the classical PSO did not meet any. Further, the hybrid approach generates a menu with the exact number type of foods from different food groups as compared to PSO in which it doesn't meet the required quantity of Go foods, Grow foods, and Vegetables.

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Table8: Analysis of the Best Solution Generated by PSO and Hybrid PSO using 1000 Generations based on the Appropriate Food Group Proportion and Required Type of Foods

Food Group	**Plate Requirements**	**Classical PSO**		**Hybrid PSO**	
		Acquired Nutrients	**Goal Achieved**	**Acquired Nutrients**	**Goal Achieved**
Appropriate Food Group Proportion					
Fruits	17%	19%	No	17%	Yes
Go	33%	30%	No	36%	No
Grow	17%	20%	No	22%	No
Vegetables	33%	31%	No	25%	No
Type of Foods					
Fruits	3	3	Yes	3	Yes
Go	3	2	No	3	Yes
Grow	3	2	No	3	Yes
Vegetables	3	5	No	3	Yes

Lastly, the classical PSO could still produce similar results. However, it would need more iterations or generations. The comparative analysis indicates that the hybrid approach has a higher chance of creating a good and acceptable solution within minimal iterations compared to classical PSO.

5.0 CONCLUSIONS

This work examines the performance of the PSO when integrated with genetic operators and fuzzy evaluation to address dietary menu planning. Results show that the PSO performs better when genetic operators are integrated into creating a dietary menu. The requirements set by Philippine Dietary Reference Intake through Acceptable Macronutrient Distribution Range (AMDR), Recommended Energy and Nutrient Intakes (RENI), and PinggangPinoy is successfully modeled and tested using Filipino recipes and ingredients available locally. Adults experiencing health problems, especially those overweight and obese, can take advantage of the results and can acquire dietary advice without difficulty. The fuzzy evaluation was successfully implemented to enable the searching process to find a more balanced food group proportion.Future research directions include consideration of the lowest cost menus and other factors like the combination of food type in one meal, the availability of the food in each Philippine region. Hence, each region produces different agricultural and livestock products, depending on their topographical conditions.

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