



Optimization Techniques and Programming for Developing Cost-Effective and Balanced Diet Schedules for Preschoolers

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Abstract

Proper nutrition is important for the growth, motor and cognitive development of young children since the foods consumed determine how well-rounded a child's diet is. However, preschool menu planning is complex because it requires balancing multiple constraints such as cost, dietary guidelines, and food variety. This study introduces a computational approach to menu planning for preschools through Linear Programming (LP), Integer Programming (IP), and Binary Programming (BP). This study highlights algorithmic design, constraint modelling, and computational efficiency in solving optimization problems, rather than focusing primarily on dietary outcomes. The models were tested using Malaysian food database to evaluate both feasibility and efficiency. The findings indicate that all models successfully fulfilled the Recommended Nutrient Intakes (RNI 2017) for children aged 4 to 6, ensuring adequate levels of energy, protein, calcium, carbohydrates, and fat. In terms of cost, the LP model was the most economical at RM4.20 per day, but impractical due to fractional servings. The IP model produced a more realistic balance between cost and practicality at RM4.40 per day. The BP model generated the most diverse and implementable menus at RM5.00 per day, though at a higher cost. Overall, these optimization methods provide decision-support tools for enhancing the efficiency of preschool menu planning.

Keywords: binary programming; integer programming; linear programming; nutrition; optimization

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1. Introduction

Planning meals for young children in kindergartens or preschools is not just about choosing tasty or healthy food but it is also about complying with a budget, avoiding repetition and meeting certain nutritional guidelines. This kind of planning can be time-consuming and complicated, especially when done manually [1]. A computer can quickly discover the most cost-effective combination of meals that meets all the requirements instead of a person having to go through menus and prices one by one. Technology can help schools and kindergartens make better, faster decisions without needing to go through trial and error.

In this study, a method from computer science called linear programming (LP) was used to make this process faster and smarter. The linear programming (LP) model is a mathematical way to find the best solution to a

problem that has a lot of rules or limitations[2]. This study explores linear programming (LP) as a means of computationally solving the preschool menu planning problem with a focus on algorithmic performance, constraint formulation, and model generalizability. The research emphasizes the applicability of LP methods as practical tools within computer science for discrete optimization in constrained environments.

While much of the existing literature in menu planning emphasizes nutritional adequacy such as caloric targets, macronutrients and micronutrients, there has been limited focus on the algorithmic and computational modelling involved. Recent studies have applied mixed-integer linear programming (MILP), goal programming, and fuzzy optimization in food service operations [3], [4]. This work is built upon foundational LP methodologies, emphasizing computational aspects

such as model efficiency, feasibility detection, and constraint optimization. It fills a gap by shifting the discussion from nutrition-driven objectives to computing-centric problem-solving.

Nutrition in early childhood plays a fundamental role in determining long-term health. Children must be fed the right proportions of food to develop and maintain their health. Preschoolers, aged four to six, require balanced diets to support physical growth, cognitive, social, and motor development as well as immune function since malnutrition among children remains a pressing public health concern, particularly during the early developmental stages of life[5]. Based on the World Health Organization, malnutrition refers to an imbalanced intake of energy or nutrients [6]. Inadequate or excessive nutrient intake at this age can lead to stunting, underweight, obesity, and various micronutrient deficiencies, which may have long-term consequences on health and learning capabilities[6] - [8].

The malnutrition problem remains the primary contributor to growth failure globally, particularly in low-income countries where stunting is a widespread public health issue linked to food insecurity. Besides, growth failure caused by malnutrition is also frequently overlooked in paediatric settings in high-income nations. Previous studies examined the current understanding of nutritional factors contributing to growth retardation among children [9],[10]. Ensuring optimal nutrition through carefully planned meals is essential to address these challenges not only for parents but also within institutional settings such as preschools and childcare centres [11] - [13].

In Malaysia, the dual burden of malnutrition is obvious, where some children suffer from undernutrition, while others face rising rates of obesity and poor dietary habits. The Ministry of Health Malaysia reported that the cases of overweight and stunted children under five years old had increased [14]. This highlights the need for structured menu planning in preschools and childcare centres. Despite the availability of the Malaysian Dietary Guidelines for Children and Adolescents (MDGCA)[15], meal planning often relies on manual practices or basic software. Recent global advancements in mathematical optimization offer promising avenues to enhance the nutritional quality and operational efficiency of such plans.

Conventional menu planning methods depend on expert knowledge, and manual iterations are time-consuming [16]. Mathematical optimization integrated with computational techniques has emerged as a valuable approach to improve the menu planning process. Researchers have applied various techniques to address the diet problem[8], [17] - [20]. For example, Stigler's diet problem model laid the foundation for using linear programming to minimize food costs while meeting nutritional requirements [21]. Several studies have demonstrated the usefulness of mathematical

approaches in formulating cost-effective and nutritionally adequate meal plans, particularly for specific groups like school children, patients, and low-income populations [22] - [24].

Since then, the application of mathematical optimization has expanded to include more advanced methods aiming to improve menu diversity, reduce cost, and incorporate real-world dietary constraints. Recent advancements in optimization techniques have been successfully applied to dietary planning problems in various contexts, including hospitals, schools, and food aid programs, primarily focusing on cost minimization and nutritional adequacy[25] - [28]. However, existing studies rarely address the unique nutritional needs of preschool-aged children, particularly within the Malaysian context, where cultural food preferences, cost constraints, and national dietary guidelines must be considered. Furthermore, many existing models overlook practical implementation aspects such as menu variety and acceptability, often resulting in repetitive or unrealistic meal plans.

This study addresses these gaps by developing an optimization-based meal planning model specifically for Malaysian preschoolers aged 4 to 6, integrating nutritional standards, cost efficiency, and menu diversity. The novelty of this study lies in its targeted demographic, its contextual adaptation to local dietary habits, and its practical applicability as a decision-support tool for school meal planning to prevent malnutrition among students. For instance, meal plans can ensure adequate levels of calcium, essential for bone development during early childhood; its deficiency is a leading cause of poor bone density and growth retardation [29], [30]. This study aims to critically assess the current state of optimization models applied to menu planning for young children, with a focus on both theoretical developments and practical implementations.

This study is important because it proves that everyday problems like meal planning can be solved more efficiently using computer-based techniques. It can also be applied to other planning tasks, such as school timetables or supply ordering, making it a useful tool beyond just food menus. This study introduces a computational approach to menu planning using linear programming, which differs from traditional methods that rely on manual or rule-based decisions. Transforming real-world constraints into a solvable optimization model enables efficient and automated planning. This work contributes to computer science by demonstrating how algorithmic techniques can solve practical problems and by paving the way for future integration with intelligent decision-support systems.

2. Methods

2.1 Research Dataset

The dataset used in this study integrates nutritional composition and cost of food items. The information of

nutritional composition is sourced from the Recommended Nutrient Intake (RNI) 2017 by the National Coordinating Committee on Food and Nutrition (NCCFN) and the Ministry of Health Malaysia [31]. The RNI 2017 outlined dietary intake recommendations for various age groups in Malaysia and included minimum and maximum nutrient values for children aged 4 to 6. Additionally, the Nutrient Composition of Malaysian Food provides detailed information on the nutritional content of foods commonly consumed in Malaysia [32]. Supplementary data were also obtained from the Malaysian Food Composition Database (MyFCD) at the website <https://myfcd.moh.gov.my>. MyFCD is an online platform which provides information from the nutrient composition book. The nutrient data can be retrieved quickly and easily using the latest technologies such as mobile devices and tablets. The current updated version of MyFCD contains 29 mandatory and 11 optional nutrients that are important to human health. It also includes the addition of 441 raw and processed foods and 668 prepared foods. Figure 1 illustrates the front page of the website Malaysian Food Composition Database (MyFCD).



Figure 1. Online Platform of Malaysian Food Composition Database (MyFCD)

The information of cost for food items are collected from online grocery platform which is Price Catcher Malaysia. Price Catcher Malaysia is a digital application that supplies current food price data at the website <https://pricecatcher.kpdn.gov.my/>. This mobile application was developed by the Ministry of Domestic Trade and Cost of Living Malaysia (KPDN) to help consumers make smarter purchasing decisions and reduce their cost of living. It allows users to check and compare daily prices of 480 basic grocery items across stores in Malaysia. It also includes a grocery list feature that identifies the most cost-effective location to purchase all listed items, promoting informed and budget-conscious shopping. Figure 2 illustrates the information on the Price Catcher Application.

The dataset used in this study consists of attributes that describe the nutritional composition and cost for each food item that are suitable for children aged 4 to 6 years aligned with the Malaysian Recommended Nutrient Intakes (RNI) 2017. These attributes are selected to ensure that the generated menus meet nutritional adequacy and cost efficiency. Table 1 shows the data structure in this study. Each row in the dataset represents a single food item and contains the following attributes.



Figure 2. The Price Catcher Application

Table 1. Data Structure

Attribute	Description
Food Item ID	Unique numerical code assigned to each food item
Food Name	The common name of the food item
Food Group	The classification of food based on Malaysian Dietary Guidelines
Energy (<i>kcal</i>)	The energy content per serving based on Malaysian Food Composition Database
Protein (<i>g</i>)	Macronutrient content per serving
Fat (<i>g</i>)	Macronutrient content per serving
Carbohydrate (<i>g</i>)	Macronutrient content per serving
Calcium (<i>mg</i>)	Micronutrient content per serving
Serving Size (<i>g</i>)	Portion size in grams based on Malaysian RNI guidelines
Cost (<i>RM</i>)	Market price per serving

2.2 Nutritional Requirements for Children

This study utilizes mathematical optimization to develop economical meal plans that satisfy both nutritional requirements and budget limitations. The 60 variables (menu items) used in this study include a range of foods that are divided into categories such as beverages, cereals/rice, meat/poultry/egg, fish, fruits, and vegetables. Table 2 shows the number of food requirements per day that consist of 6 types of food groups with the available range from the dataset of food. There are 14 dishes of food served per day for breakfast, morning snacks, lunch and afternoon snacks.

Table 2. Food Requirement per Day

Types of foods	No. of requirements per day
Beverages (x_1 - x_{10})	5
Rice/Cereals (x_{11} - x_{20})	3
Meat/poultry/egg (x_{21} - x_{30})	1
Vegetables (x_{31} - x_{40})	2
Fruits (x_{41} - x_{50})	2
Fish (x_{51} - x_{60})	1
Total dishes per day	14

Table 3. The Boundary of Daily Nutrient Intake

Nutrients	Lower Boundary	Upper Boundary
Energy (<i>kcal</i>)	1210	1300
Protein (<i>g</i>)	16	16
Carbohydrate (<i>g</i>)	130	260
Calcium (<i>mg</i>)	1000	1000
Fat (<i>g</i>)	34	51

Table 3 shows the boundaries of daily nutrient intake. 5 nutrients are considered in this study, such as energy, protein, carbohydrates, calcium and fat. Each nutrient

has a specific upper and lower boundary, except for protein and calcium, which only have a lower boundary.

2.3 Assumption and Limitations of Research

The following assumptions must be made in order to create the mathematical models in menu planning for preschool children aged 4 to 6. The assumption involved in this study are: (a) children do not have any food allergies, (b) children are healthy and do not require extra attention, (c) food on the menu is always available when needed, and (d) the prices of food remain constant.

These assumptions are necessary for model simplicity. However, certain limitations are introduced into this study. The limitation is the lack of real-world variability such as food prices fluctuation and seasonal availability which may affect the practicality of the proposed menus. Furthermore, the model does not account for the acceptability of the meals particularly for preschool children. These limitations suggest that the need for further research incorporates with real-world data, dynamic pricing and multi-objective approaches that consider both nutrition and acceptability.

While the assumptions and limitations adopted in this study enabled the development of a tractable model, they inevitably constrain the generalizability and practical applicability of the findings in real preschool contexts. For example, disregarding food allergies and health conditions overlooks children with special dietary requirements. Besides, assuming stable food availability and fixed prices overlooks the potential impact of supply chain disruptions and market volatility. Therefore, future research should address these limitations by incorporating allergy and specific constraints, individualized nutrition profiles, and robust optimization frameworks that account for uncertainty in food supply and pricing. Such extensions would enhance the adaptability and practical implementation of optimization-based menu planning in diverse institutional contexts.

2.4 Mathematical Modelling

This study uses mathematical optimization such as Linear Programming (LP), Integer Programming (IP) and Binary Programming (BP) to develop economical meal plans that satisfy the nutritional requirements needed by preschoolers aged 4 to 6. The models include the objective function, constraints and decision variables.

The objective function of this study is to minimize the cost. The general formula for the objective function is [33] Formula 1:

$$\text{Minimize cost} = \sum_{i=1}^{60} c_i x_i \quad (1)$$

c_i is the cost for each menu item and x_i is the decision variable of menu items. There are 60 variables of foods from 6 food groups.

There are two constraints involved in this study, which are nutritional requirements and food group constraints. The general formula for nutritional requirements constraint is [33] Formula 2.

$$LB \leq \sum_{i=1}^{60} w_i x_i \leq UB \quad (2)$$

LB refers to the lower boundary and UB is the upper boundary for daily recommended nutrients needed for preschoolers aged 4 to 6. While w_i is the weight of the food nutrient and x_i is the decision variable of menu items.

Next, the general formula for food group requirement constraint is [33] Formula 3.

$$\sum_{i=1}^{60} \text{Type of foods } (x_i) = n \quad (3)$$

n refers to the number of food requirements per day based on Table 2.

The combination of food with 4 different meals will appear with the decision variables from Linear Programming (LP), Integer Programming (IP) and Binary Programming (BP) [23], [24], [33] - [35]. The decision variables can be written as Formulas 4 to 6.

Linear Programming (LP), Formula 4:

$$0 \leq x_i \leq 2 \quad (4)$$

Integer Programming (IP), Formula 5:

$$x_i = \begin{cases} 1 \text{ or } 2, & \text{menu } i \text{ selected} \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

Binary Programming (BP), Formula 6:

$$x_i = \begin{cases} 1, & \text{menu } i \text{ selected} \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

The decision variables for Linear Programming (LP) are in the range of 0 and 2, while for Integer Programming (IP), the decision variables are 1 or 2, meaning that if the food items are served once or twice, otherwise it will be zero. For Binary Programming (BP), all decision variables are in binary values, 0 or 1.

Linear Programming (LP) is used for pilot studies to validate the constraints of the model and the objective function. However, because fractional servings could occur, the results might not apply to real-world situations. Binary Programming (BP) models are more suitable for scenarios where the diet plan needs to be implemented for meal planning without repetition of menus for 5 days. The LPSolve IDE software is used to solve the developed model and produce optimal solutions for a one-day menu.

2.5 Computational Approach and Reproducibility

The menu planning designed for preschool children aged 4 to 6 was formulated using Linear Programming (LP), Integer Programming (IP), and Binary Programming (BP) models through LPSolve IDE software. The nutrients and cost implemented from the Malaysian Food Composition Database (MyFCD) and dietary requirements specified in the Recommended Nutrient Intakes (RNI 2017) for children aged 4 to 6

years. Constraints were incorporated to ensure realistic portion sizes, compliance with cost boundaries, and menu diversity in models to reduce repetition.

Through LPSolve IDE, Linear Programming (LP) problems were solved using the simplex technique, an exact method for continuous optimization that efficiently identifies the optimal solution within the feasible region defined by the constraints. In contrast, Integer Programming (IP) and Binary Programming (BP) problems require discrete solutions and therefore the models are solved using the branch-and-bound technique. These strategies reduce computational complexity by systematically eliminating infeasible or suboptimal menu combinations, thus narrowing the search to solutions that still hold potential to meet all constraints and achieve the optimal objective value [36], [37].

Different with brute-force enumeration or heuristic methods in solving others optimization problem, which requires evaluating every possible combination or provide approximate solutions[38], [39]. The optimization process is deterministic, given the same input data and model specifications, the solver will consistently return identical solutions. The results are fully reproducible across computing environments as no stochastic elements were introduced and no random seeds were required. The implementation of LPSolve IDE in this study are discussed further in section (3.1).

2.6 Non-Repetitive Menu Selection Algorithm

Ensuring a variety of meals across multiple days while meeting nutritional requirements and costs is quite challenging, especially in school settings. The structured computational approach named Sufahani-Ismail Algorithm [23], [34], [36] was adapted into this study to address this issue by systematically selecting food items over 5 days without repetition, except for essential items such as plain water and plain rice, which are permitted daily due to their dietary necessity. This algorithm utilized a binary decision framework, where each selected food item is represented by a value of 1 or 0, and iteratively constructs daily meal plans that optimize for both nutritional adequacy and cost-effectiveness. However, binary models do not accommodate real-world complexities in menu planning, such as human preferences, food availability, or cultural eating habits [40].

In contrast, the Sufahani-Ismail algorithm, which was executed using LPSolve IDE software, achieved computational efficiency by narrowing the range of decision options each day. It is well-suited for precision, customizable constraints, and adaptive decision-making. A previous study of ToyBox, originally from Europe, was adapted in Malaysia to promote healthy eating habits and lifestyle among preschool children in order to prevent childhood obesity in Malaysia [41]. However, it only provides standard menu suggestions with general eating guidelines without considering the nutritional needs, food allergies

and dietary preferences. The choice of certain foods can help create better meal plans for children that lead to better nutrition and well-being for both kids and parents [42].

Figure 3 illustrates the algorithm used for non-repetitive menu selection for 5 days.

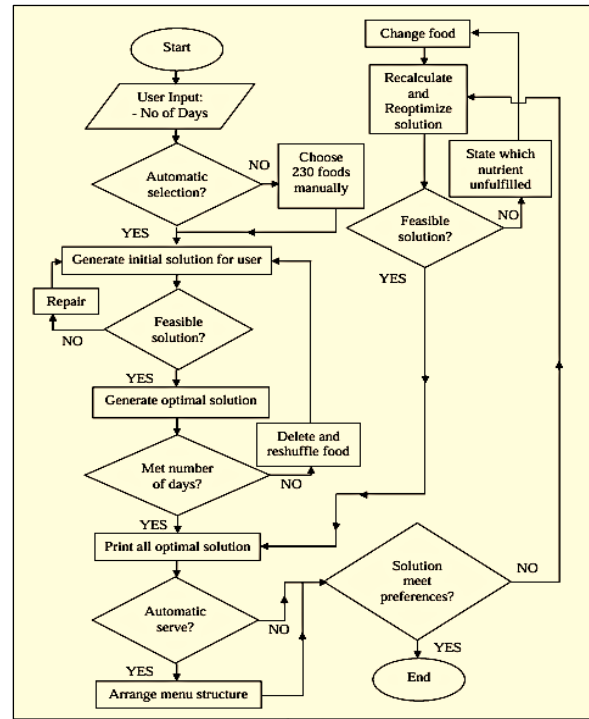


Figure 3. Sufahani-Ismail Algorithm [23]

Each type of food (except plain water and plain rice) is only allowed to be served once across 5 days. For example, on Day 1, 14 dishes from 60 menu items were chosen based on the number of food requirements in Table 2. The foods that are chosen are marked as 1 while the others are marked as 0. Before the program moves to Day 2, all the foods selected on Day 1 are removed from the list of options. The program continues this loop for all 5 days, removing previously chosen items and choosing new ones from the remaining menu items to build a meal plan. For the foods selected on any given day, their availability is reset to 0 and the menu items will not be chosen again except for plain water and rice. These selected foods are then arranged into 4 daily meals which are breakfast, morning snack, lunch and afternoon snack.

The pseudocode presented in Table 4 provides a brief structure for the algorithm to ensure that the generated menus are nutritionally balanced, cost-effective and variety [23]. The algorithm systematically selecting food items over 5 days without repetition, except for plain water and plain rice.

In conclusion, this non-repetitive menu selection algorithm represents a novel contribution to the field of menu optimization under multiple constraints, offering both structure and adaptability in meal planning systems for preschool. The algorithm also integrated

with Malaysian Recommended Nutrient Intakes (RNI) guidelines (2017) and present cultural relevance and computational flexibility personalized for Malaysian preschool nutrition.

Table 4. Pseudocode: Non-Repetitive Menu Selection Algorithm

```

(A) Input (1):
Step 1: Choose type of Serving: Manual or Automatic
Step 2: Choose number of days
(i) For 1 or 2 or 3 days, choose Automatic or Manual Selection
If Manual, then go to (B) Input (2): Option (1)
Else go to (B) Input (2): Option (2)
(ii) For 4 or 5 days, go Input (2): Option (2)

(B) Input (2):
Option (1): Manual Selection
Choose 10 BEVERAGES (including plain water),
      10 CEREALS (including plain rice),
      10 MEATS,
      10 VEGETABLES,
      10 FRUITS,
      10 SEAFOOD,
(ii) Lower Bound = zero*[1,60] matrix
(iii) Upper Bound = one*[1,60] matrix (except for plain
      water = 5 and plain rice = 5)
(iv) Food (0) = Lower Bound (food that are selected on day 0)
(v) u (0) = Upper Bound (food that are available on day 0)
(vi) d = 1@2@3@4@5 (1 or 2 or 3 or 4 or 5 days)

Option (2): Automatic Selection
(i) Lower Bound = zero*[1,60] matrix
(ii) Upper Bound = one*[1,60] matrix (except for plain
      water = 5 and plain rice = 5)
(iii) Food (0) = Lower Bound (food that are selected on day
      0)
(iv) u (0) = Upper Bound (food that are available on day 0)
(v) d = 1@2@3@4@5 (1 or 2 or 3 or 4 or 5 days)
End

```

3. Results and Discussions

This study demonstrates the effectiveness of applying optimization techniques, specifically Linear

Programming (LP), Integer Programming (IP) and Binary Programming (BP), to formulate nutritionally adequate and practical meal planning for preschoolers aged 4 to 6. The results of the models presented in this study are directly relevant to addressing malnutrition among preschool-aged children. The developed menu plan for one day meets the daily Recommended Nutrient Intake (RNI) levels for key macronutrients such as energy, protein, carbohydrate, calcium and fat, which are commonly associated with malnutrition [31]. Balancing nutrition, cost, and practicality is an important element in menu planning for preschool children.

3.1 Implementation of LPSolve IDE

The LP, IP and BP models were developed to solve the preschool menu planning problems. The decision variables represent food item selections per meal per day over a weekly cycle. The objective function in equation (1) minimizes total cost subject to nutritional requirements constraint in equation (2) and food group constraint in equation (3). This work emphasizes computational aspects such as model efficiency, feasible detection and constraint optimization. It fills a gap by shifting the discussion from nutrition-driven objectives to computing-centric problem-solving. Here are a few steps to implement the models using LPSolve IDE, which is a tool used to solve optimization problems with linear constraints and objectives.

Step 1: Install and Open LPSolve IDE

Download the software from the official website: <https://sourceforge.net/projects/lpsolve/>. Install and launch the application. Figure 4 shows the main interface of LPSolve IDE, which consists of the menu bar, toolbar and model editor panel.



Figure 4. Main Interface of LPSolve IDE

Step 2: Define the Objective Function

Start with keyword *min:* or *max:* depending on your goal. Figure 5 shows the objective function used in this study. The below command means that we want to minimize the total cost of food items $x_1, x_2, \dots, x_{60}$ with respective unit costs.

Step 3: Define the Constraints

Each constraint was written on a new line. Figures 6 and 7 present the nutritional requirements and food group constraints respectively, used in this study. The constraint for nutritional requirements is labelled with r_1 until r_5 , where r_1 represents the energy, r_2 for carbohydrate, r_3 for protein, r_4 for calcium and r_5 for fat. While constraints for food groups are labelled

with r_6 until r_12. It represents the number of food requirements per day stated in Table 2.

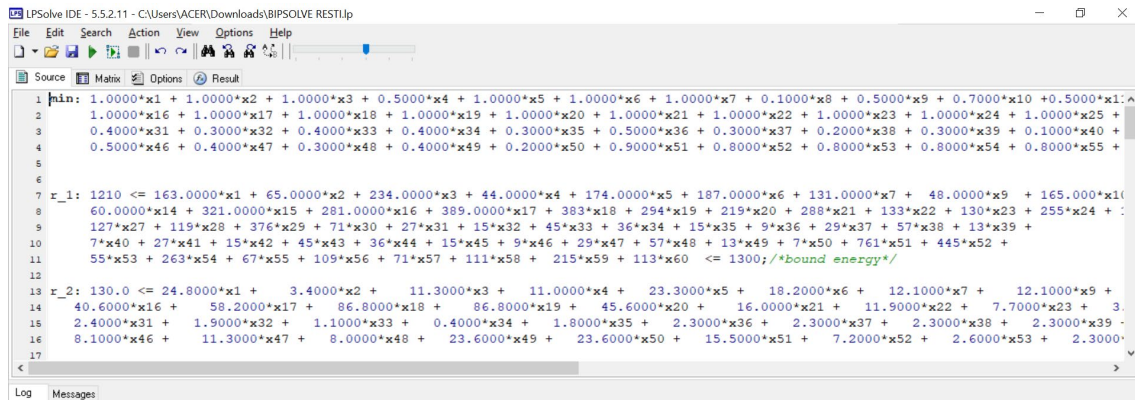


Figure 5. Define the Objective Function

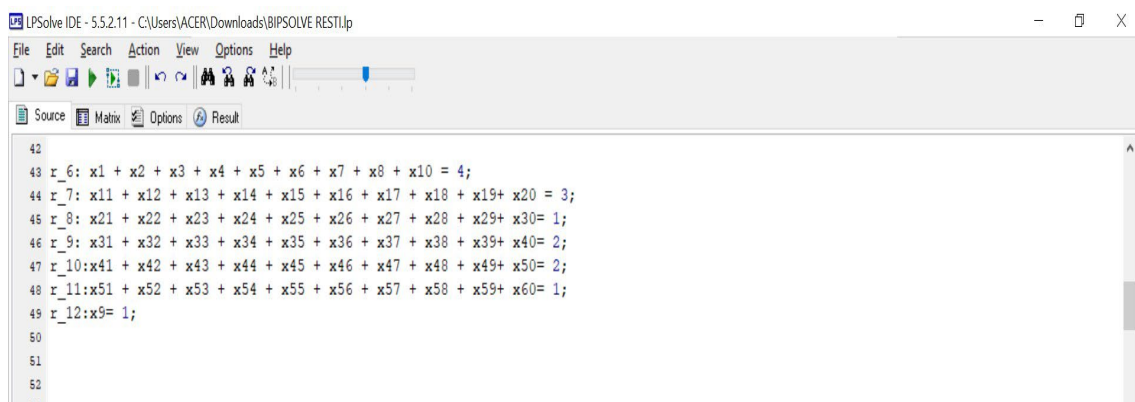


Figure 6. Nutritional Requirements Constraints

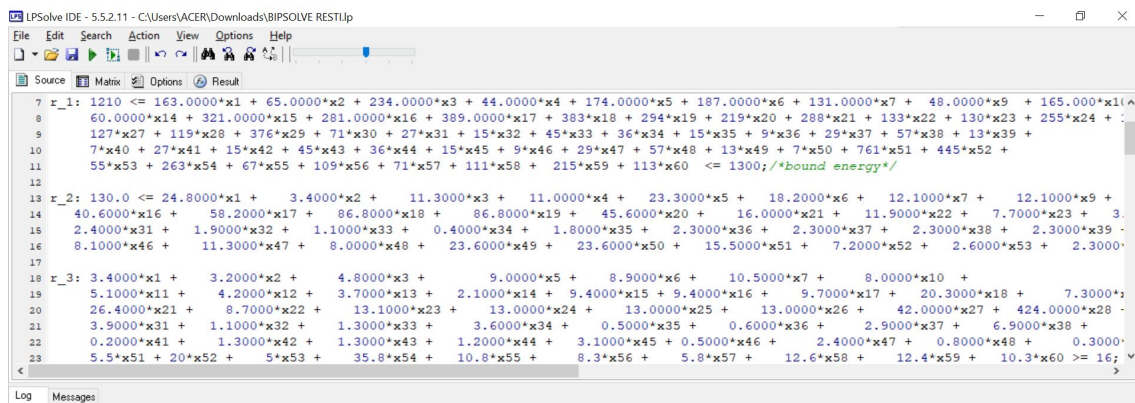


Figure 7. Food Groups Constraints

Step 4: Declare Decision Variables

The decision variables depend on equations (4), (5) and (6). Figures 8, 9 and 10 show the command of decision variables for LP, IP and BP models, respectively. The variables for LP are between 0 and 2, while IP model, the variables must be integer values and BP model, the variables are 0 or 1.

LPSolve IDE determines the optimal menu by minimizing total cost subject to nutritional requirements and food groups constraints. Linear Programming (LP) model is solved using the simplex

method, which finds the least-cost solution at the feasible boundary. While Integer Programming (IP) and Binary Programming (BP) models use branch-and-bound, which systematically explores and eliminates non-promising options, ensuring that the final solution is the exact global optimum. This guarantees that the menus generated represent the best possible outcome given the defined assumptions and constraints. The models generated cost-efficient menus in under 1 second of computation time across all test cases. Constraint satisfaction was verified in all feasible scenarios.

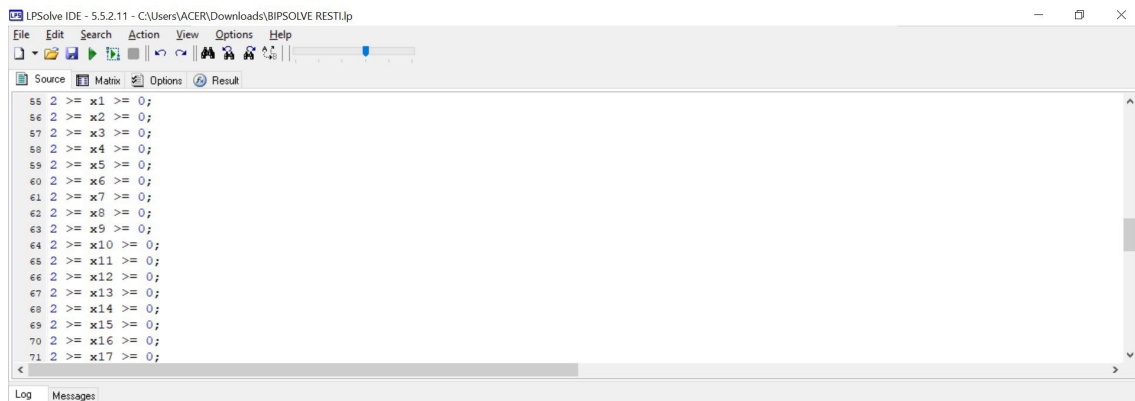


Figure 8. Decision Variables for the LP model



Figure 9. Decision Variables for the IP model

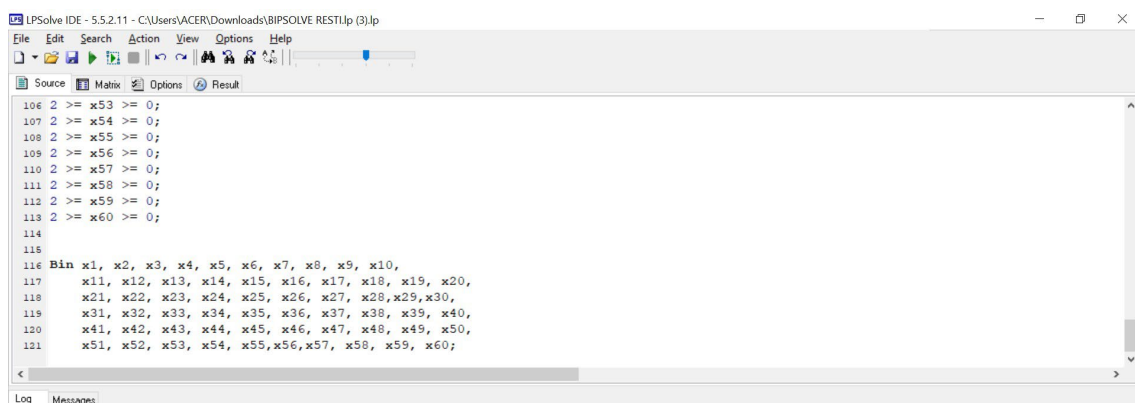


Figure 10. Decision Variables for the BP model

3.2 Results of the Optimization Models

The optimization models produced distinct outcomes in terms of cost, nutritional adequacy, and practicality of implementation. All the optimization approaches named Linear Programming (LP), Integer Programming (IP) and Binary Programming (BP) successfully generated menus that satisfied the Recommended Nutrient Intakes (RNI 2017) for preschool children aged 4 to 6. However, differences

emerged in serving patterns, cost efficiency and menu diversity.

Table 5 shows the comparison of the one-day menu based on Linear Programming (LP), Integer Programming (IP) and Binary Programming (BP) in selecting daily meals. The meals were generated by LPSolve IDE software. Each model produces different food combinations and costs based on how it handles portion quantities. Values in parentheses indicate the number of servings selected by each model. Decimal values in LP indicate fractional serving quantities,

which are not practical for implementation but help in cost optimization. The whole unit selections (0 or 1) were implemented by IP and BP models, which align better with real-world implementation. Table 5 shows that the Linear Programming (LP) model, while precise in nutrient fulfilment, suggests results in decimal values, for example, 0.044 of an egg, which is not practical for actual servings. In contrast, Integer Programming (IP) and Binary Programming (BP) models generated food quantities in whole units, making them more practical for real-world preschool settings. Additionally, the binary programming (BP) model allowed the constraints to avoid menu repetition over multiple days, which improved the dietary diversity and minimized nutrient redundancy.

Moreover, cost considerations were embedded into the models, leading to the selection of economical food options while maintaining the nutritional requirements. Based on Table 5, the optimal total cost for all three

models is less than the budget provided by the standard preschool, RM7.00 per day. The comparison of total food cost shows that the LP model offers the most cost-efficient solution at RM4.20 by allowing fractional servings, which optimizes nutrient intake at minimal expense. The IP model results in a slightly higher cost of RM4.40 due to its restriction to whole servings, making it more practical for real-world meal preparation. The BP model yields the highest cost at RM5.00, as it only permits binary decisions (0 or 1) for food selection, promoting simple and implementable menus but with less cost flexibility. The cost of food for preschoolers can vary depending on several factors. This means the preschool management will spend less than RM7.00 per person for a one-day menu. Therefore, in terms of cost, LP is cost-effective, but not always practical. BP model enhances meal diversity and enforces binary constraints, potentially improving nutritional coverage, although at a higher cost.

Table 5. Comparison of 1-day Menu Planning by LP, IP and BP Model

Meal	Linear Programming (LP)	Integer Programming (IP)	Binary Programming (BP)
Breakfast	Chocolate Malt Drink (1)	Rose Syrup Drink (1)	Full Cream UHT Milk (1)
	White Bread (1)	White Bread (1)	White Bread (1)
	Hen, egg (0.044)	Kismis (1)	
Morning Snack	Chocolate Malt Drink (1)	Chocolate Malt Drink (1)	Chocolate Malt Drink (1)
	Cream Cracker Biscuit (1)	Cream Cracker Biscuit (1)	Cream Cracker Biscuit (1)
	Plain Water (1)		
Lunch	Rice, cooked (1)	Plain Water (1)	Plain Water (1)
	Chilli Fried Mackerel, (0.956)	Rice, cooked (1)	Rice, cooked (1)
	Carrot (0.086)	Chilli Fried Mackerel, (1)	Chilli Fried Mackerel, (1)
	Spinach onion (0.914)	Soya Bean Sprout (1)	Carrot (1)
	Guava (1)		Guava (1)
Afternoon Snack	Rose Syrup Drink (1)	Chocolate Malt Drink (1)	Rose Syrup Drink (1)
	Biscuit Cream Cracker (1)	White Bread (1)	Wholemeal Bread (1)
Total Food Cost (RM)	4.20	4.40	5.00

Table 6. Comparison of Nutrient Values by LP, IP and BP Models

Nutrients	Lower Boundary	Linear Programming	Integer Programming	Binary Programming	Upper Boundary
Energy (<i>kcal</i>)	1210	1300	1218	1221	1300
Carbohydrate (<i>mg</i>)	130	209.9	208.1	181.3	260
Protein (<i>g</i>)	16	59.5	50.7	44.7	16
Calcium (<i>g</i>)	1000	1000	1042	1017	1000
Fat (<i>g</i>)	34	39.04	36	38.1	51

3.3 Nutrient Values by Optimization Approaches

Table 6 shows the results of the nutrients for a one-day menu based on the LP, IP and BP models. It shows a comparison between the lower and the upper boundary of nutrient requirements for preschoolers aged 4 to 6 based on RNI (2017) [31] and the nutrient values generated by LPSolve IDE software. The nutrient analysis highlights how each optimization model meets or exceeds the recommended dietary requirements for preschool children. All three models successfully provide energy levels within the specified range of 1210 to 1300 *kcal*.

LP achieves the maximum allowable value of energy by 1300 *kcal*. Carbohydrate intake is also well within

the acceptable range, with LP and IP delivering over 200 g, while BP offers a more moderate value of 181.3 g of carbohydrate intake, but still sufficient for daily needs. Protein values across all models far exceed the minimum requirement of 16 g, indicating the robust coverage of growth-supporting nutrients. All three meal plans provide much more protein than the minimum needed, which is a good sign because protein is important for helping children grow strong and healthy. Calcium intake meets or surpasses the 1000 *mg* boundary in all three models, ensuring bone health is adequately addressed. Lastly, fat content is well controlled across all the models, ranging from 36 g to 39.04 g and below the upper limit of 51 g. Overall, each model satisfies all the recommended nutritional

requirements for children aged 4 to 6, but the LP model tends to maximize values near the upper boundary, while the BP model offers a more balanced and implementable outcome.

The comparison in Tables 5 and 6 demonstrates that LP is optimal in cost but unrealistic to implement directly in food services. In contrast, IP provides a good balance between practicality and optimization. BP is the most straightforward and implementable, but it can be more expensive due to fixed servings or non-repetitive menu items. These understandings can help preschool administrators and nutritionists choose the right modelling strategy depending on whether cost, simplicity, or implementation ability is the primary concern in menu planning.

3.4 Sensitivity Analysis

Sensitivity analysis or post-optimal analysis is used to investigate how changes in the input data will change the optimal solution (objective function). Typically, commercial packages for solving linear programming problems include the results of such an analysis as part of the standard output report [43], [44]. However, traditional sensitivity analysis is commonly used in Linear Programming (LP), but it is not applicable for Integer Programming (IP) and Binary Programming (BP) models. Tables 7 and 8 show the output of the sensitivity analysis in LPSolve IDE for the Linear Programming (LP) model used for menu planning.

Table 7. Sensitivity Analysis for Nutrient Constraints

Constraint	Nutrient	Dual Value	From	Till
r ₁	Energy	-0.00015	1244.81	1306.15
r ₂	Carbohydrate	0	-	+
r ₃	Protein	0	-	+
r ₄	Calcium	0.00018	985.75	1151.58
r ₅	Fat	0	-	+

Table 7 presents the sensitivity analysis for the nutrient constraints in the linear programming model. The dual value of the nutrients represents how much the objective function will increase or decrease if the RHS (right-hand side) of the constraint increases by 1 unit. Energy (r₁) and Calcium (r₄) are the binding constraints as indicated by non-zero dual values, which have a significant effect on the objective function. Energy has a dual value of -0.00015, indicating that 1 unit of increment in energy will lead to a slight decrease in the objective function. While calcium has a dual value of 0.00018, increasing calcium would slightly increase the objective function. The allowable ranges for energy can vary between 1244.81 and 1306.15 kcal and calcium between 985.75 and 1151.58 mg, without changing the optimal solution. The remaining nutrients, such as carbohydrate (r₂), protein (r₃), and fat (r₅), are non-binding constraints since they have zero dual values. The changes in nutrient amount would not affect the objective function within reasonable limits.

Table 8 shows the sensitivity analysis for the objective

function coefficients of selected food items (variables). This analysis indicates the range within which the coefficient of the variable can vary without altering the optimal solution. For example, the coefficient of plain water (x₈) can change between 0.012 and 0.461, while white bread (x₁₃) can vary between 0.338 and 0.504. Variables such as egg (x₃₀), spinach onion (x₄₀), and chilli fried mackerel (x₅₉) have relatively narrow ranges, indicating that small changes in their costs or preference weights could impact the selection decision, making them sensitive items in the solution. Conversely, food items like syrup rose (x₉) and rice (x₁₁) show unlimited ranges, suggesting that their inclusion or exclusion in the menu is stable under coefficient changes.

Table 8. Sensitivity Analysis for Objective Function Coefficient

Constraints	From	Till
X ₈ (Plain water)	0.012	0.461
X ₉ (Syrup rose)	-	+
X ₁₀ (Chocolate Malt Drink)	-	0.788
X ₁₁ (Rice)	-	+
X ₁₂ (Biscuit)	-	0.362
X ₁₃ (White bread)	0.338	0.504
X ₃₀ (Egg)	0.379	0.414
X ₃₃ (Carrot)	0.362	0.478
X ₄₀ (Spinach Onion)	0.010	0.128
X ₄₄ (Guava)	-	0.203
X ₅₉ (Chilli Fried Mackerel)	0.386	0.421

Overall, this sensitivity analysis helps identify which constraints and variables are critical and which are more flexible, providing valuable insight for decision-making and robustness testing in the menu planning model. Focusing on the binding nutrient constraint, as well as the sensitive food items identified, is important to assess the stability and reliability of the menu planning solution under potential fluctuations in nutritional requirements or food item weights.

4. Conclusions

This study demonstrates the power of linear programming (LP), integer programming (IP) and binary programming (BP) in addressing real-world planning problems beyond traditional applications. We illustrated how the models can serve as a robust engine for optimization under multiple constraints by conceptualizing preschool menu planning into constraint-driven computational problems. It also explored the application of optimization techniques in preschool meal planning as a strategic response to address malnutrition among young children. The findings demonstrate how structured, data-driven decision-making can enhance dietary adequacy while balancing cost, nutritional needs, and institutional constraints by integrating mathematical models. It also emphasizes the potential of these methods to assist policymakers, nutritionists, and school administrators in developing meal plans that meet the essential nutrient requirements of preschoolers. Moreover, the flexibility of optimization models allows for adaptation to local food availability, cultural preferences, and

budgetary limitations, making them a powerful tool in the broader fight against child malnutrition.

Future research may expand on this work by incorporating real-time data and personalized school feeding programs. This model can also be part of a larger information system. For example, researchers can integrate with a school canteen management system and develop a parents' application to track a child's diet at school. Besides, integration of machine learning with linear programming can also be conducted for demand forecasting or exploring hybrid metaheuristic models to handle larger datasets. In addition to the present findings, this study also opens opportunities for broader applications. The proposed model can be integrated into real-time school meal planning systems to support administrators and nutritionists in making data-driven decisions on a daily basis. Furthermore, the framework can be extended into a multi-objective optimization approach to ensure nutritional adequacy and cost-effectiveness as well as promoting greater menu diversity and acceptability among children. These highlight the practical relevance and scalability of the model, paving the way for future research and real-world implementation in educational settings. In conclusion, optimization techniques could play a vital role in improving the nutritional status and well-being of children across the country by continuing to refine these techniques and addressing real-world challenges.

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