Problem Chosen	2026 MCM/ICM Summary Sheet	Team Control Number
A		0000000

Summary

Keywords:

Contents

1 Introduction

1.1 Background

The Mobile Food Pantry (MFP) program, operated by the Food Bank of the Southern Tier (FBST), serves as a critical lifeline for food-insecure populations across six counties in New York State. By 2019, the program had achieved significant operational maturity, maintaining a network of 70 regular sites and conducting 722 annual distributions. However, the global shock of the COVID-19 pandemic exposed profound vulnerabilities within food supply chains and service delivery frameworks[1]. While regional resilience varied, the pandemic forced the FBST to significantly contract its service coverage and overhaul its operational models.

As the public health situation stabilizes, FBST aims to restore its service capacity to pre-pandemic levels in 2021, including the removal of pre-registration requirements. The central challenge now lies in leveraging 2019 historical data to design a robust site-visit scheduling scheme. This scheme must achieve a delicate balance between demand alignment, social equity, and operational feasibility, while simultaneously accounting for the stochastic nature of weather conditions and the optimization of volunteer resources. Addressing these complexities is essential for ensuring the efficient delivery of food assistance and effectively meeting the heightened needs of the community.

1.2 Restatement of the Problem

Considering the background information and constraints specified in the problem statement, we are tasked with addressing the following four objectives:

- Develop an effective and fair 2021 visitation schedule based on the total community demand surrounding the 70 regular sites, ensuring that all clients are served on average and significant service disparities are minimized.
- Modify the existing scheduling approach by selecting one of two strategies: 'reducing serviced sites while optimizing locations' or 'maintaining current sites while adjusting visitation timing', based on historical weather-driven demand fluctuations.
- Design an algorithm for the one-truck-two-sites operational model, determining site pairings, scheduling dates, and initial site food distribution volume, and evaluate the effectiveness and equity of the distribution.
- Compose a one-page executive summary that articulates the primary advantages and potential limitations of the proposed recommendations for the Food Bank's leadership.

1.3 Literature Review

1.4 Our Work

2 Assumptions and Justification

3 Notations

4 Model I: Bi-Objective Site Visit Frequency Allocation and CP-SAT Periodic Scheduling Model

4.1 Model Overview

4.2 Model Building

In prioritizing our dual objectives, we place fairness at the forefront of our strategy. Research indicates that society should prioritize eliminating poverty through resource allocation rather than merely pursuing organizational capacity expansion[2]. If effectiveness were prioritized over fairness, vulnerable populations at low-demand or remote sites would face the risk of marginalization, which directly contradicts the core organizational mission of FBST. By establishing fairness as a prerequisite—guaranteeing that basic needs are met before optimizing resource distribution—the model achieves a necessary balance between social value and operational efficiency.

4.2.1 Dual-Fairness Guided Frequency Allocation

To scientifically determine the annual visit frequency k_{i_e} for each site, this study constructs a dual-fairness allocation mechanism focusing on Coverage Equity and Demand-Adaptive Equity.

We prioritize Coverage Equity as the essential foundation for demand-adaptive equity, ensuring fundamental service access for all recipients. Research indicates that efficiency-driven algorithms often exacerbate regional service disparities [5]. In the context of food assistance, over-emphasizing matching efficiency can systematically marginalize remote or low-demand communities. Therefore, a targeted coverage mechanism is vital to rectify geographic biases and ensure accessibility for vulnerable populations, directly fulfilling the inclusive mission inherent in the FBST project [4].

(1) Coverage Equity

We first set a baseline service guarantee k_{base}, representing the minimum annual visits per site. As a decision variable, and referring to the 2019 average frequency, we set the range for k_{base} as $[5, 10]$. The residual allocation capacity N_{free} is calculated as:

$$N_{free} = N_{total} - 70 \times k_{base} \tag{1}$$

where $N_{total} = 730$ is the total annual service capacity for 2021.

(2) Demand-Adaptive Equity

Residual capacity N_{free} is allocated using the historical aggregate demand ratio as the weight. The annual aggregate demand for site i is $D_i = n_i d_i$. Consequently, the final allocated annual visit frequency k_{i_e} for site i is calculated as:

$$k_{i_e} = k_{base} + \text{round}\left(N_{free} \times \frac{n_i d_i}{\sum_{i=1}^{70} n_i d_i}\right) \tag{2}$$

This formula ensures baseline service for all sites while allowing high-demand sites to receive more frequent visits, thus balancing coverage and precision.

4.2.2 Effectiveness Quantification and Impact Analysis of Baseline Frequency

This study establishes the precise alignment of supply and demand as the primary criterion for effectiveness. Accordingly, we construct a quantitative scoring model and utilize it to analyze the underlying impact patterns of the baseline service frequency on effectiveness. The specific details are presented as follows:

(1) Effectiveness Utility Score

Step 1: Calculate Total Annual Effective Supply. Considering the vehicle capacity constraint $d_0 = 250$, the effective supply for site i is:

$$annual\_eff_i = k_{i_e} \times \min(d_i, d_0) \tag{3}$$

Step 2: Define Imbalance Penalties. The unmet demand rate and resource wastage rate are defined respectively as:

$$unmet_i = \frac{\max(0, D_i - annual\_eff_i)}{D_i} \tag{4}$$

$$waste_i = \frac{\max(0, k_{i_e} \times d_0 - D_i)}{k_{i_e} \times d_0} \tag{5}$$

Step 3: Comprehensive Effectiveness Score. The utility score is obtained as:

$$score_i = \frac{annual\_eff_i}{D_i} - \alpha \cdot unmet_i - \beta \cdot waste_i \tag{6}$$

Based on the project's inclusive goals, the social harm of undersupply is significantly higher than that of resource waste. Therefore, we set the shortage penalty coefficient $\alpha = 0.5$ and the surplus penalty coefficient $\beta = 0.2$.

(2) Impact of baseline service frequency on Effectiveness

By comparing the system's effectiveness performance under various values of k_{base}, the following core patterns are identified:

- **As the baseline service frequency increases, the average effectiveness score of the sites exhibits an upward trend:**The baseline guarantee mechanism strengthens resource allocation toward low-demand sites, effectively mitigating the risk of undersupply for these locations. Furthermore, because the model assigns a higher penalty weight to supply shortages, the improved scores of low-demand sites directly drive the growth of the overall average effectiveness score.

- **The total effective supply follows an inverted U-shaped trend:** When k_{base} remains within a reasonable range, the baseline guarantee provides a safety net for essential services at low-demand sites while preserving sufficient residual capacity for high-demand areas, leading to steady growth in total effective supply. However, an excessively high k_{base} forces a substantial portion of transport capacity to be allocated to sites with minimal demand, thereby crowding out resources intended for high-demand locations. This results in an expanding supply gap at high-demand sites, ultimately causing a decline in the system's total effective supply.

4.2.3 Secondary Validation of Equity via Gini Coefficient

The aforementioned analysis indicates that the principle of fairness in public welfare projects is manifested not only in the overall equity of resource allocation but also in the balanced effectiveness of services across various sites. To precisely quantify the disparities in effectiveness scores among the 70 sites, this paper introduces the Gini coefficient(G) as an evaluation metric for fairness:

$$G = \frac{\sum_{i=1}^{70}\sum_{j=1}^{70}|score_i - score_j|}{2 \times 70^2 \times \overline{score}} \tag{7}$$

where $G \in [0, 1]$. A value closer to 0 indicates higher equilibrium. We set a fairness threshold of $G < 0.2$. The k_{base} that satisfies this threshold while maximizing the total score is selected to determine the final k_{i_e}. To clarify the logical chain of dual-fairness frequency allocation and effectiveness evaluation, the operational mechanism of the mobile pantry scheduling model is visualized in the following flow chart:

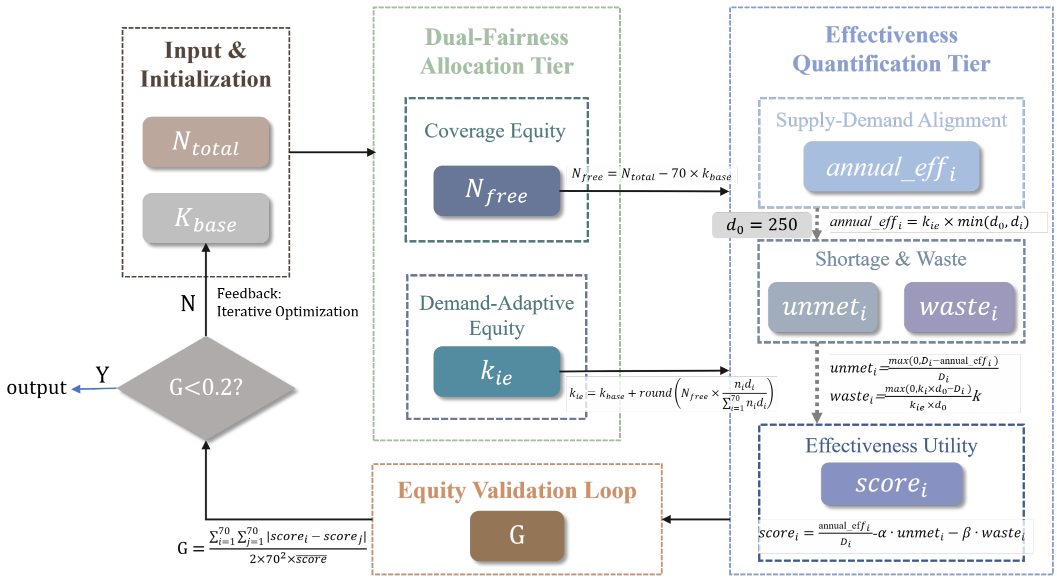

Figure 1: Dual-Fairness Allocation and Effectiveness Quantification Mechanism

4.3 Model Solution

4.3.1 Periodic Scheduling Model

This stage addresses the operational execution: "When should each site be visited?" We define this as a combinatorial optimization problem aimed at uniform visit distribution.

Decision Variables:

- $s_{i,m}$: The scheduled service date for the m-th visit to site i.
- $a_{i,t}$: A binary assignment variable where $a_{i,t} = 1$ if site i is visited on day t, and 0 otherwise.

Objective Function: The objective is to minimize the total absolute deviation between actual intervals and the ideal recurrence interval $T_i = 365/k_{i_e}$:

$$\min Z = \sum_{i=1}^{70} \sum_{m=1}^{k_{i_e}-1} |(s_{i,m+1} - s_{i,m}) - T_i| \tag{8}$$

Constraints:

1. **Daily Capacity Constraint:** Total visits per day must not exceed the maximum truck capacity: $\sum_i a_{i,t} \leq 2$ [1].
2. **Frequency Requirement:** Each site must be visited exactly k_{i_e} times: $\sum_t a_{i,t} = k_{i_e}$.
3. **Minimum Revisit Interval:** Based on the 14-day food support cycle: $s_{i,m+1} - s_{i,m} \geq 14$.

4.3.2 Solution via CP-SAT Solver

Traditional Mixed-Integer Linear Programming often struggles with large-scale scheduling due to high search costs. In this study, we utilize the Google OR-Tools CP-SAT solver. Leveraging its lazy clause learning mechanism, CP-SAT significantly prunes the search space for infeasible solutions. Its "freezing" functionality allows for local refinements on top of global optimization, ensuring high-quality, actionable schedules for large-scale operations.

References

[1] Shenggen Fan et al. "Food system resilience and COVID-19 – Lessons from the Asian experience". In: *Global Food Security* 28 (2021), p. 100501. ISSN: 2211-9124.

[2] Mohammad Firouz et al. *On the Equity-Efficiency Trade-off in Food-Bank Network Operations*. 2021.

[3] Weiguo Liu, Zhaoping Chen, and Yin Zhang. *Matlab program design and application*. In Chinese. Beijing: Higher education press, 2002.

[4] Seyed Bagher Hashemi Natanzi et al. *FairShare: Auditable Geographic Fairness for Multi-Operator LEO Spectrum Sharing*. 2026.

[5] Ariana Tang et al. *Contextual Budget Bandit for Food Rescue Volunteer Engagement*. 2025.

Enjoy Your Bath Time!

From simulation results of real-life situations, we find it takes a period of time for the inflow hot water to spread throughout the bathtub. During this process, the bath water continues transferring heat into air, bathtub and the person in bathtub. The difference between heat transfer capacity makes the temperature of various areas to be different. So that it is difficult to get an evenly maintained temperature throughout the bath water.

In order to enjoy a comfortable bath with even temperature of bath water and without wasting too much water, we propose the following suggestions.

- Adding hot water consistently
- Using smaller bathtub if possible
- Decreasing motions during bath
- Using bubble bath additives
- Arranging more faucets of inflow

Sincerely yours,

Your friends

Appendices

Appendix A First appendix

In addition, your report must include a letter to the Chief Financial Officer (CFO) of the Goodgrant Foundation, Mr. Alpha Chiang, that describes the optimal investment strategy, your modeling approach and major results, and a brief discussion of your proposed concept of a return-on-investment (ROI). This letter should be no more than two pages in length.

Here are simulation programmes we used in our model as follow ([3]).

Input matlab source:

```
function [t,seat,aisle]=OI6Sim(n,target,seated)
pab=rand(1,n);
for i=1:n
    if pab(i)<0.4
       aisleTime(i)=0;
    else
        aisleTime(i)=trirnd(3.2,7.1,38.7);
    end
end
```

Appendix B Second appendix

some more text **Input C++ source:**

```
//===========================================================================
// Name        : Sudoku.cpp
// Author      : wzlf11
// Version     : a.0
// Copyright   : Your copyright notice
// Description : Sudoku in C++.
//===========================================================================

#include <iostream>
#include <cstdlib>
#include <ctime>

using namespace std;

int table[9][9];

int main() {

    for(int i = 0; i < 9; i++){
        table[0][i] = i + 1;
    }

    srand((unsigned int)time(NULL));

    shuffle((int *)&table[0], 9);

    while(!put_line(1))
```

```
    {
        shuffle((int *)&table[0], 9);
    }

    for(int x = 0; x < 9; x++){
        for(int y = 0; y < 9; y++){
            cout << table[x][y] << " ";
        }

        cout << endl;
    }

    return 0;
}
```

Report on Use of AI

1. OpenAI ChatGPT (Nov 5, 2023 version, ChatGPT-4,)

   Query1: <insert the exact wording you input into the AI tool>

   Output: <insert the complete output from the AI tool>

2. OpenAI Ernie (Nov 5, 2023 version, Ernie 4.0)

   Query1: <insert the exact wording of any subsequent input into the AI tool>

   Output: <insert the complete output from the second query>

3. Github CoPilot (Feb 3, 2024 version)

   Query1: <insert the exact wording you input into the AI tool>

   Output: <insert the complete output from the AI tool>

4. Google Bard (Feb 2, 2024 version)

   Query1: <insert the exact wording of your query>

   Output: <insert the complete output from the AI tool>