

Tradeoff between Geographic and Demographic Equity in Food Bank Operations

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Abstract

According to Feeding America, prior to the pandemic, 1 in 5 African-American/Black, 1 in 6 Hispanic, and 1 in 4 Native American households were food insecure compared to 1 in 11 White households. The pandemic is expected to exacerbate these disparities given its disproportionate economic and health impact on historically marginalized racial and ethnic populations. Food banks are non-profit organizations that work to alleviate food insecurity within their service regions by distributing donated food to households in need. Equitable distribution of donated food is an important criteria for food banks. Existing food banking operations literature primarily focus on geographic equity, i.e., where each geographic block of a food bank's service region receives food in proportion to its demand. However, hunger-relief organizations such as food banks are gradually incorporating demography-based equity in their distribution of donated food in light of the disparities that exist within different demographic groups, such as race, age, and religion. However, the notion of demographic equity has not received attention in the food banking operations literature. This study aims to fill in the gap by developing a multi-criteria optimization model to identify optimal distribution policies for a food bank considering a two-dimensional equity criterion, geographic and demographic, in the presence of effectiveness (undistributed food minimization) and efficiency (distribution cost minimization) criteria. We apply the model to our partner food bank's data to (i) explore the trade-off between geographic and demographic equity as a function of effectiveness, and efficiency, and (ii) identify policy insights.

Keywords— Food Insecurity; Racial Equity; Geographic Equity; Food banks; Multi-criteria optimization

1 Introduction

Food insecurity, defined by a household's inability to access sufficient food to ensure normal growth and nourishment for its members, is a significant problem in the US [1]. In 2019, [2] reported that 35 million people in the US were food insecure (with low or very low food security), which was the lowest overall food insecurity level in more than twenty years. However, the COVID-19 pandemic significantly increased food insecurity. More than 60 million people turned to food banks and community programs to put food on the table in 2021 [2]. In addition, [1] showed that there remains a persistent gap in the prevalence of food insecurity between people of color and White people in the US. Moreover, the pandemic disproportionately increased food insecurity among communities of color, who were already facing hunger at much higher rates before the pandemic. [2] projects that 21.6% of African-American households (1 in 5) may have experienced food insecurity in 2020, compared to 12.3% (1 in 8) of White households in the US.

In the US, food banks, which work to alleviate food insecurity, are an integral part of the supply chain receiving and distributing donated food in an equitable, effective (minimizing undistributed food), and efficient (minimizing distribution cost) manner [3]. While many studies in the food banking operations management literature consider equity, they have focused primarily on geographic equity, where each geographic region (e.g., service planning area) receives food proportional to their demand. However, there exists a significant gap in developing optimal distribution policies for food banks that consider demographic equity, i.e., where each demographic group receives food proportional to their demand. As a step toward filling this gap, we develop a multi-criteria optimization model that considers both the geographic and demographic equity, in the presence of effectiveness (undistributed food minimization) and efficiency (distribution cost minimization). Specifically, we develop a single-period, two-echelon, multi-criteria linear programming model that considers four criteria in the objective function: geographic equity, demographic equity, effectiveness, and efficiency. We

apply the model on our partner food bank's data to: (i) explore the trade-offs between geographic and demographic equity as a function of effectiveness, and efficiency, and (ii) identify policy insights. We show that our model is able to improve the efficacy of the distribution policies in terms of geographic and demographic equity.

2 Related Research

The food banking operations management literature focuses on developing tactical distribution policies for food banks within their service regions (e.g., geographical areas such as counties). In this literature, the criteria of equity, effectiveness, and efficiency are commonly considered criteria. [4] developed a deterministic, capacity-constrained network flow model considering equity and effectiveness. Perfect equity is achieved when each area within a food bank's Service Region receives food proportional to their demand. Effectiveness refers to maximizing the distributed pounds of food, i.e., minimizing undistributed food. [5] allow for the absolute deviation from perfectly equitable distribution for each area of the service region to be bounded above by a user-defined value. [6] developed a two-stage stochastic model to incorporate stochastic receiving capacity, whereas [7] developed a robust optimization model to incorporate uncertainty. [8] developed a discrete-time discrete-state Markov Decision Process (MDP) model with stochastic supply where they define equity as a function of the Pounds distributed Per Person in Poverty (PPIP) across the food bank's service region. [3, 9] included effectiveness and efficiency in the objective, while implementing equity as a constraint. They defined equity as the sum of absolute difference in the proportion of demands fulfilled between pairs of geographical areas within the food bank's service region. [10] studied a similar model structure, where they defined effectiveness as nutritional service maximization. [11] considered all three criteria simultaneously in the objective function as a weighted sum and developed a novel algorithm to elicit food bank managers' preference over the criteria. To the best of our knowledge, our study is unique in its consideration of two-dimensional equity in the food banking operations literature. However, methodologies for improving racial equity can be seen in healthcare research. For example, [12] and [13] developed machine learning and non-linear programming-based methods to improve the equity in waiting times for the patients in hospitals. To the best of our knowledge, our paper takes the first step to incorporate the notion of demography-based equity in the optimal tactical distribution policy for food banks.

3 Model

In this study, we consider a food bank that has a single warehouse where donations are received. The food bank is assumed to serve a "Service Region" which is composed of a set of "Service Areas" (SA), i.e., geographic regions. The Los Angeles Regional Food Bank (LARFB) is an example of a food bank with this structure. LARFB's Service Region is Los Angeles (LA) county which is divided into eight Service Areas, referred to as Service Planning Areas (SPA). The food bank distributes donated food to the service areas. Within the food bank's service region, the food insecure population can be divided into multiple demographic groups based on the social identities of the population, such as race, age, or religion. A food bank's objective is to distribute the available food donation equitably across the service areas (geo-equity) and demographic groups (demo-equity) while minimizing the undistributed food (effectiveness) and the cost of distribution (efficiency). We develop a single-period, multi-criteria linear programming model named "M4". Model M4 considers the sum of four scalarized criteria in the objective function - geo-equity, demo-equity, effectiveness, and efficiency - subject to a supply constraint at the food bank. Table 1 contains the notation for Model M4. The model is formulated as follows.

$$\begin{aligned}
 \text{Model} \quad & \text{M4} \\
 \text{Min} \quad & f_1 + f_2 + f_3 + f_4 & (1) \\
 \text{s.t.} \quad & Y \leq S & (2) \\
 & y_{ij} \geq 0, \forall i \in \mathbf{I}, \forall j \in \mathbf{J} & (3)
 \end{aligned}$$

Here, f_i represents the scalarized criterion i , where $i = 1, 2, 3, 4$ represents geo-equity, demo-equity, effectiveness, and

Table 1: Notations

Field	Description	Unit
<i>Sets</i>		
I	Set of Service Areas (SA), where $\mathbf{I} \equiv \{1, \dots, i, \dots, I \}$	
J	Set of demographic groups (DG), where $\mathbf{J} \equiv \{1, \dots, j, \dots, J \}$	
<i>Parameters</i>		
d_i	Distance between the hub and SA $i \in \mathbf{I}$	(miles)
δ_{ij}	Demand of DG $j \in \mathbf{J}$ in SA $i \in \mathbf{I}$	(lbs)
$geo\delta_i$	Total demand of SA $i \in \mathbf{I}$, ($= \sum_{j \in \mathbf{J}} \delta_{ij}$)	(lbs)
$demo\delta_j$	Total demand of DG $j \in \mathbf{J}$, ($= \sum_{i \in \mathbf{I}} \delta_{ij}$)	(lbs)
$geop_i$	Geo-Demand Proportion of SA $i \in \mathbf{I}$, ($= \frac{geo\delta_i}{\sum_{i \in \mathbf{I}} geo\delta_i}$)	
$demo p_j$	Demo-Demand Proportion of DG $j \in \mathbf{J}$, ($= \frac{demo\delta_j}{\sum_{j \in \mathbf{J}} demo\delta_j}$)	
S	Total available supply at the hub	(lbs)
c_s	Per-mile cost of distribution for one pound of food	$\left(\frac{\$}{lb \cdot mile}\right)$
c_h	Holding cost per pound of food	$\left(\frac{\$}{lb}\right)$
<i>Decision variable(s)</i>		
y_{ij}	Pounds of food to be distributed from hub to DG $j \in \mathbf{J}$ in SA $i \in \mathbf{I}$	(lbs)

efficiency, respectively. Constraint 2 ensures that the food bank cannot distribute more than its available supply. Here, $Y = \sum_{i \in \mathbf{I}} \sum_{j \in \mathbf{J}} y_{ij}$. In the following section, each criterion is introduced and formulated.

3.1 Non-scalarized Criteria for Distribution

Before we present the non-scalarized formulations for each of the criteria, we define the collective attributes for the decision variables: $Y_i = \sum_{j \in \mathbf{J}} y_{ij}$; $Y_j = \sum_{i \in \mathbf{I}} y_{ij}$.

Geographic and Demographic Equity (π_1 and π_2): Geographic equity, Equation 4, is defined as the absolute difference between the amount of food distributed to SA i and their proportion of the total supply based on the SA's relative proportion of the total demand (geo-fairshare). Similarly, demographic equity, Equation 5, is defined as the absolute difference between the amount of food distributed to demographic group j and their proportion of the total supply based on their DG's relative proportion of the total demand (demo-fairshare).

$$\pi_1 = \sum_{i \in \mathbf{I}} |Y_i - geop_i \cdot Y| \quad (4)$$

$$\pi_2 = \sum_{j \in \mathbf{J}} |Y_j - demo p_j \cdot Y| \quad (5)$$

A distribution policy is defined as perfectly geographically equitable if each SA receives food in proportion to the demand associated with their geographic region (geo-demand), i.e., geo-fairshare. A distribution policy is defined as perfectly demographically equitable if each demographic group receives food in proportion to the demand associated with their particular demographic group, i.e., demo-fairshare. The non-scalarized formulations of the geo-equity and demo-equity criteria are defined by the minimization of the sum of absolute deviations between the pounds received by each SA and DG, and their geo-fairshare for all SAs and demo-fairshare for all DGs, respectively.

Effectiveness and Efficiency (π_3 and π_4): The non-scalarized formulation for the effectiveness criterion, Equation 6, is defined as the minimization of the undistributed food. The non-scalarized formulation for the criterion of efficiency, Equation 7, is defined as the minimization of cost of distribution. The criterion value is calculated by multiplying the per mile cost of food distributed per pound with the total distance covered and the amount of food distributed.

$$\pi_3 = c_h \cdot (S - Y) \quad (6)$$

$$\pi_4 = c_s \cdot \left(\sum_{i \in \mathbf{I}} d_i \cdot Y_i \right) \quad (7)$$

3.2 Criteria Scalarization

Model M4 is a multi-criteria optimization problem where the different criteria have different units and scales. This approach becomes problematic when all the criteria are combined, where the model focuses on minimizing the criteria with higher

ranges and neglect the other criteria to minimize the overall objective function value. To solve this issue, we scalarize each criterion using Linear Normalization to scale each criteria between 0 and 1 [11]. This technique utilizes the best and worst-case of the criteria in the following way:

$$f_i = \frac{\pi_i - \pi_i^b}{\pi_i^w - \pi_i^b} \quad (8)$$

where π_i^b and π_i^w are the best and worst-case scenarios for each criteria $i \in \{1, 2, 3, 4\}$, respectively. The best value for each criteria is zero. To calculate the worst-case scenarios for the criteria, we have used the methods developed by [11].

4 Results

Case Study: The Network of Los Angeles Regional Food Bank (LARFB): We have applied Model M4 to the network of LARFB. The network consists of eight Service Planning Areas (SPA) in Los Angeles county, i.e., eight Service Areas, and a single hub which is located in SPA 4 (Metro), (the network is shown in Figure 1(a)). We consider six racial and ethnic groups as our demographic groups: Latino, White, African-American, Native Alaskan, Asian, and Other. The demographic characterization by racial and ethnic group within each SPA can be found in Figure 1(b). We consider the year 2015 as the study period for the model, when the LARFB hub received a total of 70,314,382 pounds of food donations. We identify the demand weighted SPA centroids and considered the hub to be on the centroid of the SPA 4 to calculate the great-circle distances. We use 374.4 pounds per person in need as estimated by [9]. To estimate the demand of each SPA, the pounds per person in need is multiplied by the food insecure population of each SPA. To estimate the demand by racial or ethnic group j , we identify the LA-county food insecure population of race j and multiply it by 374.4 pounds [9]. Then, we estimate the demand proportion of SPA i (race j) by dividing its demand in pounds with the total demand of all SPAs (all races). The demand proportions of SPAs 1 through 8 are 0.046, 0.206, 0.133, 0.128, 0.068, 0.115, 0.144, and 0.160, respectively. The demand proportions by racial and ethnic group are: Latino - 0.674 ; White - 0.147; African-American - 0.109; Asian - 0.066; Native Alaskan - 0.003; and Other - 0.001. From LARFB's data, we estimate the holding and per mile cost of distributing one pound distribution costs: c_h as 0.27 \$/lb and c_s as 0.20 \$/lb-mile.

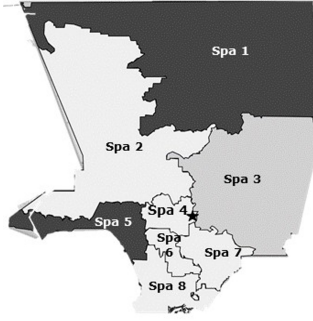


Fig: (a)

SPAs	Total Population	Food-insecure Population	Population count by race					
			Latino	White	African-American	Asian	Indian/Alaskan	Other
SPA 1	397,272	136,662	178,772	139,045	63,564	15,891	1,589	795
SPA 2	2,248,311	611,541	899,324	1,011,740	89,932	247,314	4,497	2,248
SPA 3	1,814,459	395,552	834,651	381,036	72,578	526,193	3,629	1,814
SPA 4	1,191,772	381,367	619,721	297,943	59,589	214,519	2,384	1,192
SPA 5	667,220	203,502	106,755	427,021	40,033	93,411	1,334	667
SPA 6	1,050,698	340,426	714,475	21,014	294,195	21,014	1,051	2,101
SPA 7	1,320,945	427,986	964,290	184,932	39,628	118,885	2,642	2,642
SPA 8	1,569,560	475,577	627,824	455,172	235,434	235,434	3,139	12,556

Fig: (b)

Figure 1: Los Angeles County and its constituents SPAs (Fig (a)) and their demographic details (Fig (b))

Discussion: To observe the impact of the inclusion of demo-equity criterion (f_2), we take a step-by-step inclusion process. First, we consider only geo-equity (f_1) and effectiveness (f_3), which results in the distribution of all food with perfect geo-equity at the expense of high distribution cost. However, this distribution policy results in high demographic inequity, as depicted in Table 2 which reports the absolute percentage deviation of each racial group's demo-equity. When we include efficiency (f_4), the model distributes all available food with lower cost by distributing more food to the closest SPA and less to the furthest. However, high demographic inequity still prevails in this policy (Table 2). In contrast, we can see a significant improvement in demographic equity across the six racial and ethnic groups when we include f_2 in the objective function as shown in bold in Table 2. We take a similar approach to observe the impact of the inclusion of geographic equity criterion (f_1). When we consider f_2 and f_3 , the model produces a perfectly demo-equitable distribution of all available food, with high geo-inequity as shown in Table 4 which reports the absolute percentage deviation from perfect geo-equity for each SPA. Inclusion of f_4 produces a similar result, but with all food being distributed to the closest SPA to

minimize distribution cost (Table 3). In contrast, a better geo-equitable solution is produced when f_1 is considered (Table 4). Here, six out of eight SPAs achieve perfect equity, but the SPA with shortest distance from the hub receives more than its fairshare, whereas the SPA with maximum distance receives less. Geo-equity is associated with efficiency as achieving geo-equity may result in distributing significant pounds to the SPA with largest distance. However, demo-equity has no such association as food can easily be redistributed among the closest SPAs and the model can still be demo-equitable without compromising efficiency. This is the reason, we infer, Model M4 can achieve demo-equity easier than geo-equity.

Table 2: Impact of demo-equity inclusion

Criteria Included	Latino	White	African-American	Asian	Indian/Alaskan	Others
1,3	76%	100%	95%	30%	19287%	100%
1,3,4	76%	100%	95%	100%	20819%	100%
1,2,3,4	0%	0%	0%	0%	0%	0%

Table 3: Impact of geo-equity inclusion

Criteria Included	SPA 1	SPA 2	SPA 3	SPA 4	SPA 5	SPA 6	SPA 7	SPA 8
2,3	137%	100%	100%	15%	99%	546%	98%	100%
2,3,4	100%	100%	100%	679%	100%	100%	100%	100%
1,2,3,4	91%	0%	0%	33%	0%	0%	0%	0%

To shed more light on the impact of geo-equity and demo-equity on each other, we develop constrained versions of Model M4. We consider either scalarized geo-equity (f_1) or demo-equity (f_2) as constraints, where the criterion is bound by a value between $[0,1]$. We vary the bound from 0 to 1 with a step size 0.01 and observe how the other criteria values change. Figure 2(a) and Figure 2(b) show the evolution of the criteria values as the bounds on f_1 and f_2 evolves, respectively. From Figure 2(a), we can see that when the bound on f_1 is zero, the model generates perfectly demo-equitable policy with high shipping cost. However, as the upper bound on f_1 increases, the shipping cost decreases by distributing more to the closer SPAs. Once the upper bound reaches a threshold of 0.46, efficiency (f_4) value converges to zero and remain unchanged as the bound increases to 1. Furthermore, the policy remains perfectly demo-equitable as it is easier for the model to achieve. From Figure 2(b), we can observe that the model sacrifices geographic equity to maintain lower shipping cost when the bound on f_2 is zero. However, as we increase the bound, the model produces geo-equity by increasing the shipping cost a bit. At the f_2 bound threshold of 2×10^{-8} , the distribution policy becomes perfectly geo-and-demo-equitable.

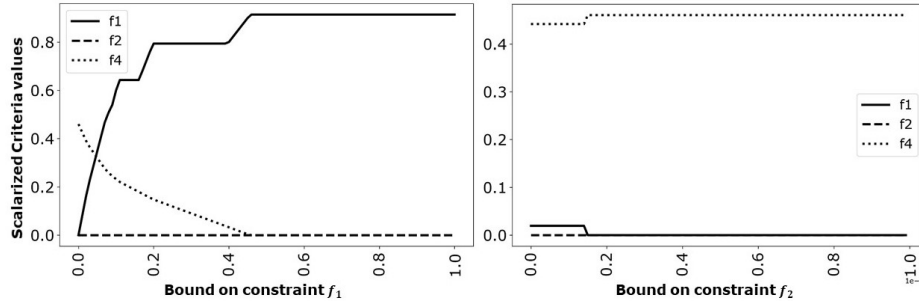


Figure 2: Changes in the scalarized criteria values as bounds change on constraints f_1 (Fig (a) - left) and f_2 (Fig (b) - right)

5 Conclusion

In this paper, we have studied the impact of considering demographic equity on the distribution of donated food by a food bank. Our research has been motivated by the existing disparity in food insecurity among different racial and ethnic groups in the US. We have considered a food bank that distributes donated food within a service region, divided into a set of service areas. We have developed a single-period multi-criteria linear programming model to produce geographic and demographic equitable distribution of the donated food across the service areas for a food bank while minimizing the undistributed food and distribution cost. We have shown that neglecting one of the equity criterion can result in inequity. We have also numerically identified thresholds for geographic and demographic equity where significant changes occur

in the distribution policy. In future, we plan to explore additional measures of equity to achieve more equitable policies within geographic regions and further model the interaction of geographic and demographic divisions of a food bank's service region.

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