MODELS FOR FOOD RESCUE AND DELIVERY: ROUTING AND RESOURCE ALLOCATION PROBLEM

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ABSTRACT

Food rescue and delivery program helps to alleviate hunger by rescuing the unspoiled surplus food that would have otherwise found its way to landfill, and distributing it to people in need. This is a large scale collection, distribution and inventory management problem and is challenged by numerous operational issues. The gap between the food recovered (supply) and the delivery request (demand) has increased the attention on the effectiveness and the equitable allocation of rescued food. The rescue and the delivery of food surplus should meet several criteria such as minimizing routing costs and waste as well as ensuring an equitable distribution of the resources collected among welfare agencies. Specifically, the traditional cost minimizing approach in pickup and delivery operations focuses mainly on efficient routing, and may lead to an inequitable distribution of the rescued food. In this paper, we propose two additional objective functions designed to promote their social interest, fair and equitable resource allocation within the food rescue program: maximize the total satisfaction of delivery customers (welfare agencies) and maximize the satisfaction of the least satisfied delivery customer. Both objectives are combined with the traditional transportation cost minimization to provide balanced solutions. We explore the behavior and the performance of the proposed models as well as the satisfaction of the welfare agencies and the structure of the obtained routes. We compare the ability of the proposed models to enhance the equitable distribution of rescued food without losing sight of the transportation costs.

Keywords: vehicle routing problem, unpaired pickup and delivery, food rescue and delivery, fair optimization

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1. INTRODUCTION

While about 805 million of the 7.3 billion people in the world live in hunger, 98.26 percent of the hungry people live in developing countries representing 13.5 percent of their population *(1).* On the other side contradicting this fact, 230 million tons of food is wasted or disposed in landfill every year *(2).* This worldwide hunger and food waste problem is confronted by an ever-growing number of food rescue organizations who collect surplus food from different food providers (supply customers) and redistribute it to welfare agencies supporting various forms of food relief. With increased shortage of food and poverty, capturing safe and nutritious food that would have been laid to waste and directing them to the vulnerable population through innovative transportation methods addresses the research priorities. The problem described in this paper is driven by the food rescue operations in Australia. Hunger remains a largely hidden social problem in a food secure nation like Australia. Even though Australia is a great food-producing country and is capable of feeding almost twice as the current estimated population of about 36.24 million people, recent research shows a contradiction, that over 2 million people have low food security *(3).* Sadly, food rescue programs are the primary source of food for these 2 million people, including children and old age people, who live with low food security. The efficiency of food rescue operations depends on effective utilization of rescued food with minimum wastage. The operations of these food rescue organizations are challenged by numerous operational issues. Gap between the demand and supply, limited transport resources, the perishability of rescued food and lack of storage space are some of them. The significant gap between the food recovered (supply) and the delivery request (demand) of welfare agencies has increased attention on the effectiveness of the rescued food allocation policies.

The problem described in this paper is motivated by food rescue organization OzHarvest, one of the largest food rescue organization in Sydney. OzHarvest is the first perishable food rescue organization in Sydney, founded in 2004, that rescues 56 tonnes of surplus food every week from different food providers, including grocery, supermarket, cafes, farmers, wholesalers, small vendors, restaurants etc. and directly delivering at no charge to agencies providing assistance to vulnerable men, women and children. The data collected from the food rescue organization show that the food recovery network is characterized by high volume collection and distribution of surplus food which is uncertain and shows variation in time and space. The network consists of around 500 food providers and more than 250 recipients distributed over an area of 12,000 square kilometres. They operate 13 truck routes, each visiting 10 to 20 food providers and 10 to 15 agencies daily. The trucks start from the depot, collect surplus food from the food providers, deliver it to agencies, depending on their delivery demand and return to the depot at the end of their journey. The delivery demand of an agency can be met using the surplus food collected from one or more food providers. And hence the food rescue and delivery problem can be formulated as an unpaired pickup and delivery problem, a variant of the well-known vehicle routing problem.

Unlike other organizations, the logistic operations of not-for-profit food rescue organizations are not only cost driven. They operate in the social interest, equity and fairness. Precisely, they operate in a social environment in which they often take difficult decisions regarding an efficient and equitable redistribution of rescued food to the hungry. Much research has been conducted on related problems in profit organizations where the objective is to maximize the profit or minimize operations cost. However, little work has been conducted in not-for-profit logistics. The contribution of the paper will be towards developing vehicle routing models that address the major concerns of food rescue and delivery problem, the fair and equitable distribution of surplus food and minimization of waste. Further, accounting for equity can help enable societal transformation to enhance

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sustainability and wellbeing. Specifically, the improvement of logistics of food rescue and delivery can aid in reducing overall food waste generation as well as better analysis and optimisation of mobility of surplus food to the vulnerable population of the country.

The remainder of the article is structured as follows. In Section 2 we review the related literature and identify the research gaps. In Section 3, we propose two novel objective functions and models for food rescue organizations: maximize the total satisfaction of delivery customers (welfare agencies) and maximize the satisfaction of the least satisfied delivery customer. The impact of these objectives on the structure of the routes, behavior and performance of the models and the satisfaction of agencies are discussed in Section 4 using instances created from the benchmark Pickup and Delivery Vehicle Routing Problem (PDVRP) instance introduced by Breedam *(4)* and an instance representative of OzHarvest operations. Finally, we conclude the paper and discuss future research directions in Section 5.

2. LITERATURE REVIEW

Despite its wide applicability routing problems received less attention in charity operations. Earlier studies focused on delivery network of meals-on-wheels program *(5).* Several studies were conducted to explore the potential use of a GIS in improving the efficiency of pre-cooked meals delivery network *(6-7).* Later they extended their work by generalizing the problem as Home Delivered Meals-Location Routing Problem (HDM-LRP) and proposed meta-heuristics to solve the location routing problem (8-9). Later on the delivery network of food bank started getting attention due to the complexity in their operations, while most of the studies focused on location routing models *(10-11).* The unpaired PDVRP *(12-18)* first appeared in literature as one commodity pickup and delivery travelling salesman problem, which can be found in many real world applications like transportation of milk, sand, gas, eggs, vaccines, etc. However unpaired PDVRP never appeared in the literature in the context of food rescue and delivery to the best of our knowledge.

There is a growing literature that addresses equity and fairness in non-profit sector. Most of the work focuses on humanitarian logistics, where they minimize the unsatisfied demand of all aid recipients *(19-21).* An extensive review is provided in *(22).* Some papers *(23-26)* explored different social welfare utility functions as an indicator of equity and fairness and were used as an additional objective in multi-objective models. They show that the choice of objective function has significant impact on the routing structure and the resource allocation. A few studies addressed the need of equitable allocation policies in food relief programs *(25-26).* A sequential resource allocation model for food rescue program at Chicago aimed at the effective and equitable allocation of rescued food. They considered egalitarian welfare utility function as an indicator of equity. However, the routes were designed based on the assumption that all the food providers were visited before visiting the agencies which is not true in all food rescue and delivery operations. Although these studies provided insight into various food relief efforts, the equitable and effective food relief was not addressed completely.

3. FOOD RESCUE AND DELIVERY PROBLEM

As discussed in Section 1 the delivery demand of an agency can be met using the surplus food collected from one or more food providers. And hence the food rescue and delivery problem can be formulated as an unpaired pickup and delivery problem, a variant of the well-known vehicle routing problem. The food rescue and delivery problem is defined on a graph $G = (N, A)$.

N : set of customers such that $N = \{0,1,\dots,n,n+1,\dots n'\}$,

N_p : set of pickup customers such that $N_p = \{1, \dots, n\}$,

N_d : set of delivery customers such that $N_d = \{n+1, \dots, n'\}$,

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N_c : set of nodes representing all the customers such that $N_c = \{N_p \cup N_d\}$,

A : set of all arcs such that $A = \{ (i, j) : i, j \in N, i \neq j\}$,

c_{ij} : the nonnegative cost associated with each arc that designates the Euclidean travel distance from customers *i* to *j*, where, $i \neq j$, $c_{ij} \neq 0$ and $c_{ij} = c_{ji}$ for every *i* and *j*.

K : set of homogenous vehicles with identical capacity such that $K = \{1, ---, k\}$

C_k : capacity of each vehicle *k*,

T_k : tour length of each route *k*,

S_i : pickup demand (supply) associated with pickup customers $i \in N_p$

R_i : delivery demand(request) associated with delivery customer $i \in N_d$

3.1. Assumptions

We make the following assumptions:

- vehicles start and end at the depot node labelled 0,
- each customer node is visited exactly once by one vehicle,
- vehicles pickup and deliver a single product,
- the supply and request of depot is assumed to be null,
- the surplus food picked up from the pickup customers can be delivered to any delivery customers,
- the surplus food collected from pickup customers and not delivered to delivery customers are considered as waste,
- the supply of any pickup node does not exceed the capacity of the vehicles,
- the vehicle does not return to depot for loading or unloading the product,
- the surplus food accumulated on the vehicle does not exceed the capacity of the vehicle,
- the maximum number of routes planned per day does not exceed the number of vehicle.
- the total distance travelled by a vehicle on its route does not exceed the maximum tour length limit.

3.2. Decision Variables

(i) Delivering rescued food among the agencies:

d_{ik} : d_{ik} is the quantity of rescued food that can be delivered to the agency $i \in N_d$ by a vehicle k and it varies from *0* to R_i. The satisfaction of delivery customers is defined as a ratio of d_{ik} and R_i. As d_{ik} tends to R_i, the satisfaction criterion improves

(ii) Vehicle routing decision variables:

x_{ijk} : x_{ijk} is 1 if arc (i,j) is an optimal solution, otherwise 0. Where i and j are customers visited by vehicle k.

l_{ik} : l_{ik} is the load of vehicle *k* while leaving node *i*

u_{ik} : u_{ik} correspond to the position of node *i* in the route.

3.3. Objective Functions

Objective 1 (Z_0)*:* aims at minimizing the total travel cost in visiting the pickup and delivery customers.

$$Minimize \sum_{k \in K} \sum_{(i,j) \in A} c_{ij}\, x_{ijk} \qquad (1)$$

Objective 2 (Z_1*):* (Utilitarian) aims at maximizing the total satisfaction (utility) of the delivery customers.

$$Maximize \sum_{i\in N_d}\sum_{k\in K}\frac{d_{ik}}{R_i} \tag{2}$$

Objective 3 (Z_2): (Egalitarian/max-min) aims at maximizing the satisfaction of the least satisfied delivery customer and forces a vehicle not to necessarily satisfy a customer's entire demand but rather to save supply to serve another customer.

$$Maximize\ \min\left\{\sum_{k\in K}\frac{d_{ik}}{R_i}\ : i\in\ N_d\right\} \tag{3}$$

3.4.Constraints

$$\sum_{k\in K}\sum_{j\in N, i\neq j} x_{ijk} = 1 \qquad \forall\ i\ \in N_c \tag{4}$$

$$\sum_{k\in K}\sum_{j\in N, i\neq j} x_{jik} = 1 \qquad \forall\ i\ \in N_c \tag{5}$$

$$\sum_{j\in N, i\neq j} x_{ijk} - \sum_{j\in N, i\neq j} x_{jik} = 0 \qquad \forall\ i\ \in N\ , k\ \in K \tag{6}$$

$$\sum_{i\in Nc} x_{0ik} \leq 1 \qquad \forall\ k\ \in K \tag{7}$$

$$\sum_{(i,j)\in A} c_{ij}\, x_{ijk} \leq\ T_k \qquad \forall\ k\ \in K \tag{8}$$

$$l_{0k}\ = 0 \qquad \forall\ k\ \in K \tag{9}$$

$$l_{jk}\ \geq\ (l_{ik}\ + S_j\ )\, x_{ijk} \qquad \forall\ i\in N, j\in N_p,\ k\ \in K \tag{10}$$

$$l_{jk}\ \geq\ (l_{ik}\ -\ d_{jk}\ )\, x_{ijk} \qquad \forall\ i\in N\ , j\in N_d, k\ \in K \tag{11}$$

$$S_i \leq\ l_{ik} \leq\ C_k \qquad \forall\ i\in N_p\ , k\ \in K \tag{12}$$

$$0 \leq\ l_{ik} \leq\ \ C_k -\ d_{ik} \qquad \forall\ i\in N_d\ , k\ \in K \tag{13}$$

$$u_{0k} = 1 \qquad \forall\ k\ \in K \tag{14}$$

$$u_{ik} - u_{jk}\ + (|N|-1)\, x_{ijk}\ \leq\ |N|-2 \qquad \forall\ (i,j)\ \in Ac,\ \ k\ \in K \tag{15}$$

$$2 \leq u_{ik} \leq |N| \qquad \forall (i,j)\ \in Ac, k\ \in K \tag{16}$$

Constraints (4) and (5) ensure that each customer node is visited exactly once. Equality (6) represents flow conservation. Inequality (7) imposes the depot requirements that each vehicle starts and ends at the depot and it is not necessary that all the vehicles must leave the depot, Constraint (8) ensures that the distance travelled by the vehicle does not exceed the maximum tour length limit. Equations (9) - (11) identifies the load on vehicle while leaving each node and ensures that the load on the vehicle throughout the route is consistent with the pickup and delivery requests. Constraints (12) and (13) ensure feasibility with respect to capacity and (14) - (16) represents Miller Tucker Zemlin (MTZ) sub-tour elimination constraint.

4. NUMERICAL STUDY

In this section we illustrate the impact of equity objectives on the structure of the routes, behavior and performance of the models and the satisfaction of agencies using a 6 node test instance and instances created from benchmark instance. Also, we discuss the bi-objective models that combine the equity objectives and traditional transportation cost minimization objective to provide balanced solutions.

4.1. Equity Objectives

In this section we illustrate the differences between the optimal solutions obtain with the proposed objective functions using a small instance. Consider an instance with 2 vehicles with a capacity of 30 units each, 3 pickup customers (1, 3, 5), 3 delivery customers (2, 4, 6) and a depot (0) as shown in figure 1(a) Travel costs are taken as the Euclidean distance between the customer nodes. Figure 1(b-d) presents the optimal solutions obtained for each objective function considered in the study. The figure shows the optimal routes denoted by π_k, waste (w), deficit (l) in each route, delivery amount (d_{ik}) at each delivery customers and their satisfaction level (s_i).

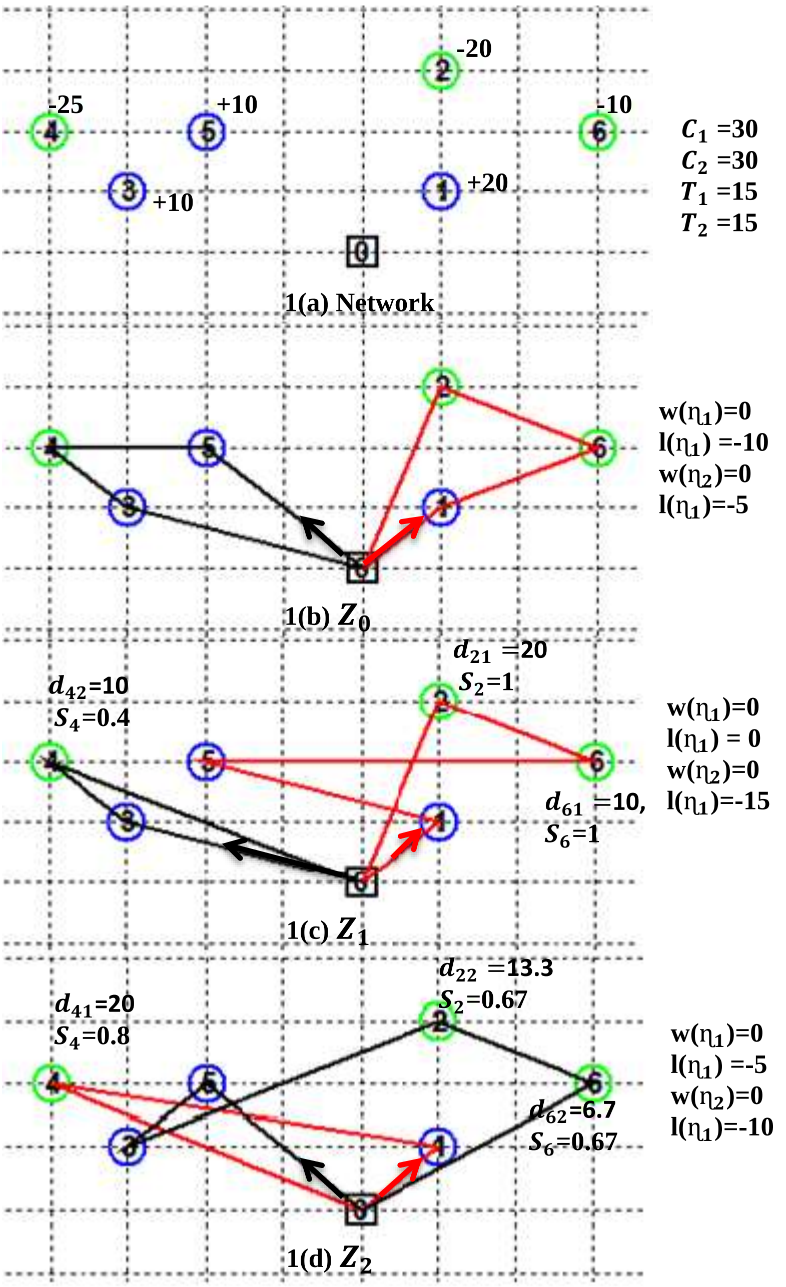

FIGURE 1 Test Instance And Optimal Solutions.

TABLE 1 Test Instance - Optimal Solutions Under Different Objectives

Optimized objective function	Transportation cost (Z_0)	Total satisfaction (Z_1)	Satisfaction of least satisfied customer (Z_2)
Z_0	18.45	1.9	0.4
Z_1	22.63	2.4	0.4
Z_2	19.18	2.13	0.67

Table 1 shows the optimal solution obtained solving each objective function and the values of other compromised objective function. It can be seen that the transport cost minimizing approach (Z_0) which focuses only on efficient routing, leads to less satisfaction of customers and inequitable distribution of rescued food. Although both Z_1 and Z_2 aims at maximizing equity and distribution, the two different objective functions lead to a different optimal solution and route structure.

In the case of objective Z_1, the first vehicle, visits customers 1, 5, 6 and 2 and the second vehicle visit customers 3 and 4. Even though the total satisfaction is 2.4 the s_i values of customers 2, 4 and 6 are 1, 0.4 and 1 respectively as shown in figure 1(c). This leads to an inequitable distribution of the rescued food. The satisfaction level of customer 4 can be improved by swapping customers 4 and 6 between vehicle 1 and 2. In the case of Z_2, the first vehicle, visits customers 1 and 4 and the second vehicle, visits customers 5, 3, 2 and 6. The total satisfaction of the food delivery system is 2.13 and is inferior compared to the one of the optimized functions Z_1, but the satisfaction level of customers 2, 4 and 6 are 0.67, 0.8 and 0.67 respectively as shown in figure 1(c).

The equity in satisfaction is high in Z_2 when compared to Z_1. Also, there is a significant difference in the rate structure. In Z_1, vehicle 1 visits pickup customers 1 and 5 before visiting delivery customers 6 and 2 and vehicle 2 visits pickup customer 3 before visiting delivery customer 4. In Z_2, vehicle 1 visits pickup customers 1 deliver it to customers 4 and vehicle 2 visits pickup customer 5 and 3 and delivers it to delivery customer 2 and 6.

4.1.1. Performance of small instances.

We now consider 15, 20, 25 and 30-node instances created from a 100-node benchmark instance for PDVRP for non-homogenous demand introduced by Breedam (4). Since the focus of the problem considered in the study is route efficacy and equitable distribution of supply (which is assumed to be inferior to the demand), instances were created randomly with fixed pickup and delivery customer ratio,r_1 and total supply to demand ratio, r_2 and is represented as (17) and (18).

$$r_1 = \frac{|N_p|}{|N_d|} \tag{17}$$

$$r_2 = \frac{\sum_{i \in N_p} S_i}{\sum_{j \in N_d} R_j} \tag{18}$$

r_1 is the ratio of number of pickup customers to the number of delivery customers and is selected as 0.4, 0.5 and 0.6. r_2 Is the ratio of the total amount of product picked up from the pickup customers to the total request of delivery customers and the value is selected between 0.6 and 0.8 to match with the problem studied. Vehicles have a capacity of 100 units and the tour length is fixed based on the size of the instance and feasibility of routes. Travel costs are taken as the Euclidean distance between the customer nodes.

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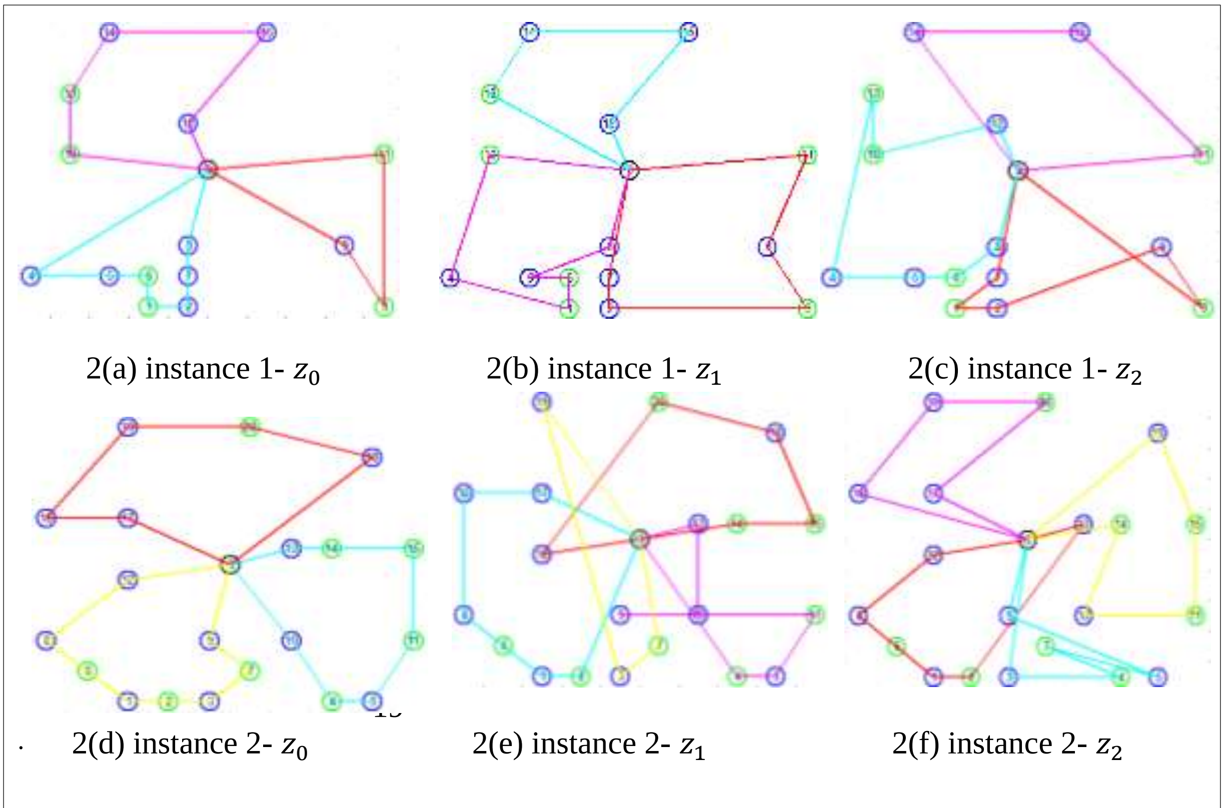
TABLE 2 Summary of Optimal Solutions Under Different Objectives

Instance		Z_1 (S_i)				Z_2 (S_i)			
Customers	Dataset	Min	Avg	Max	Total	Min	Avg	Max	Total
20 customers	1	0	0.64	1	9	0.38	0.46	1	6.375
	2	0	0.75	1	9.75	0.5	0.63	1	8.25
	3	0	0.79	1	9.5	0.5	0.625	1	7.5
25 customers	1	0	0.64	1	11	0.6	0.61	0.8	10.4
	2	0	0.73	1	11.75	0.6	0.62	0.9	9.9
	3	0	0.76	1	12.25	0.6	0.6	0.6	9.6
30 customers	1	0	0.75	1	15	0.6	0.6	0.6	12
	2	0	0.75	1	14.25	0.58	0.61	1	11.58
	3	0	0.75	1	14.25	0.6	0.63	0.9	12

The models are solved using AMPL/CPLEX on a 64-bit Inter core i5 machine with 2.4 GHz processor *(27-28)*. Small instances up to 15 nodes were solved to optimality and the maximum computational time was less than 300 seconds. 20, 35 and 30 node instances were solved with a time limit of 1200 seconds. Table 2 presents the aggregate results of all instances which coincide with the observations detailed before. Fairness and equity is achieved when the satisfaction of least satisfied customer is equal to the average satisfaction of the system (all customers) and it can be seen in the optimal solution obtained using objective function Z_2. Figure 2 presents the optimal solution obtained after solving a 15 node instance (instance 1 – r_1= 0.6 and r_2= 0.69) and a 20 node instance (instance 2 – r_1= 0.6 and r_2= 0.71).



2(a) instance 1- z_0 2(b) instance 1- z_1 2(c) instance 1- z_2

2(d) instance 2- z_0 2(e) instance 2- z_1 2(f) instance 2- z_2

FIGURE 2 Instance 1 And 2 - Optimal Solutions.

The results also show that the optimal solution is sensitive to the number of vehicles. In most of the cases, optimizing Z_0 results in minimum usage of vehicles and is not the same with Z_2 and Z_1. And hence a sensitivity analysis is performed to better understand the nature of the problem and behavior of the solution relative to variation in the number of vehicles

4.1.2. Sensitivity Analysis

We consider a instances with 15, 20 and 25 customers to study the sensitivity of optimal solution towards the number of vehicles. The number of vehicles is taken as 3, 4 and 5 in each case. Table 3 shows the summary of optimal solutions and the number of vehicles used in each cases. While objective function Z_0 minimizes the total transportation cost (and consequently the number of vehicles used), Z_1 and Z_2 attempts to maximize the satisfaction and equity irrespective of the number of vehicles used. The results show that the optimal solutions are sensitive towards the number of vehicles used. In the case of 15 and 25 customers, instances maximum satisfaction is obtained when the number of vehicles used is 4 and 5. Also, in the 25 customer instance, Z_2 improves with the usage of more number of vehicles. This is due to the additional tour length constraint, which restricts the solution space. However, with 20 customers Z_1 and Z_2 show no improvement with regards to the increase in the number of vehicles. Further, in this case, allowing more vehicles leads to the usage of the maximum number of vehicles, although there is no improvement in the equity objectives.

TABLE 3 Optimal Solution – Sensitivity Analysis

Instance	K	Number of vehicles used			Z_0	Z_1	Z_2
		Z_0	Z_1	Z_2			
15 customers	3	3	3	3	482.74	3.5	0.5
	4	3	4	4	482.74	4.25	0.5
	5	3	5	5	482.74	4.25	0.5
20 customers	3	3	3	3	511.86	6	0.5
	4	3	4	4	511.86	6	0.5
	5	3	5	5	511.86	6	0.5
25 customers	3	2	3	3	493.35	12	0.6
	4	2	4	4	493.35	12.25	0.6
	5	2	5	5	493.35	12.25	0.63

4.2. Bi-objective Models

The numerical study discussed in Section 4 clearly shows the significance of equity and satisfaction objectives in food rescue and delivery problem. And hence we propose two bi-objective vehicle routing models to extend the classic cost minimizing problem. Each model features an equity objective discussed in section 3.3 along with traditional cost minimizing objective. We compare the ability of models to enhance the equitable distribution of rescued food without losing sight of the initial objective minimizing transportation cost. Minimizing transportation cost is considered as a primary objective in both the models. The bi-objective models considered are:

Model 1(S_1): Objective 1: Z_0.
Objective 2: Z_1.
Model 2(S_2): Objective 1: Z_0.
Objective 2: Z_2.

Since no solution can be obtained optimizing both the objectives simultaneously, we adopt an ε-constraint approach to find Pareto-efficient solutions between the conflicting

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objectives. The ε-constraint method tries to search for an acceptable trade-off between the objectives by passing one of the objectives into a constraint. We transform the equity objective into constraint and the S_1 can be written as

$$Minimize \quad Z_0 \tag{18}$$

Subject to: constraints (4) - (16). and

$$Z_1 \quad \geq \epsilon_1 \tag{19}$$

S_2 can be written as

$$Minimize \quad Z_0 \tag{20}$$

Subject to: constraints (4) - (16). and

$$Z_2 \quad \geq \epsilon_2 \tag{21}$$

4.2.1Illustration Using Small Instance

We consider the same 15 customers instance to illustrate the bi-objective models. The number of vehicles is set to 4. As we know the optimal solution for Z_1 and Z_2, at $k = 4$ is 4.25 and 0.5, the initial values of ϵ_1 and ϵ_2 is set to 0.425 and 0.5. Then the ε values are gradually decreased to find the optimal solution Z_0. The trade-off between cost objective Z_0 and the equity objectives Z_1 and Z_2 obtained for the models S_1 and S_2 are presented in Figure 3. The improvement of one objective is seen to deteriorate the other. Point A on the approximation of Pareto - curves (obtained by interpolating the points in the Pareto-curve), represents minimum transportation cost, point B represents maximum satisfaction and point C represents a trade- off between transportation cost and satisfaction Once we have the approximated Pareto-curve, point C can be selected based on the preference and requirements of food delivery operations.

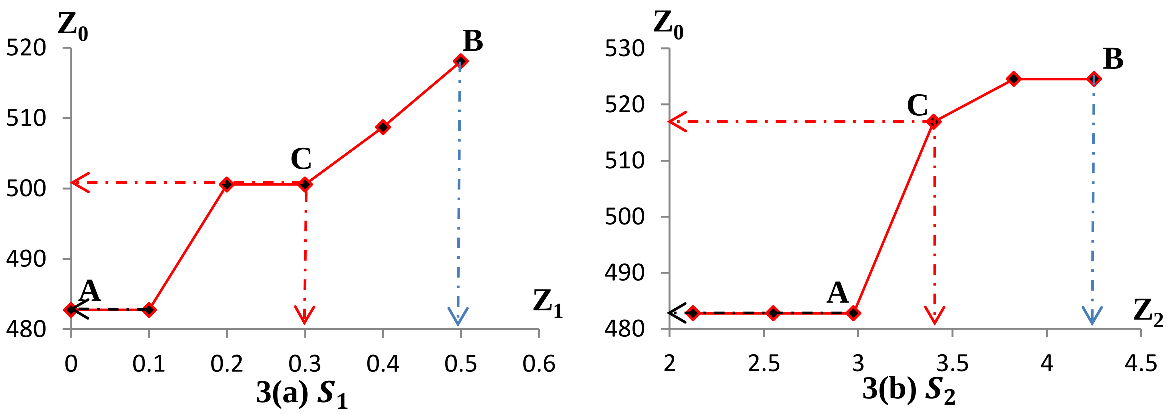

FIGURE 3 Trade –off- curve.

4.3. Case Analysis of Food Relief Operation

The case study focuses on OzHarvest-food rescue organization in Sydney, Australia. The network consists of around 500 food providers and more than 250 recipients distributed over an area of 12,000 square kilometres. Due to the large network size, the collection and distribution area have been divided into five regions, Sydney city, south east, north west, north east and south west. The inward and outward flow of each region is managed individually. The impact of objectives in food relief routing and equitable distribution of rescued food is analyzed by solving the VRP models using OzHarvest food rescue and delivery data of a randomly selected day. The pickup demand is set to the quantity of food collected from the food providers. Since the data regarding delivery request were not available, it is set to the average food delivered to the agencies. The food relief network consists of 170 customers and one depot including 133 pickup customers and 37 delivery customers.

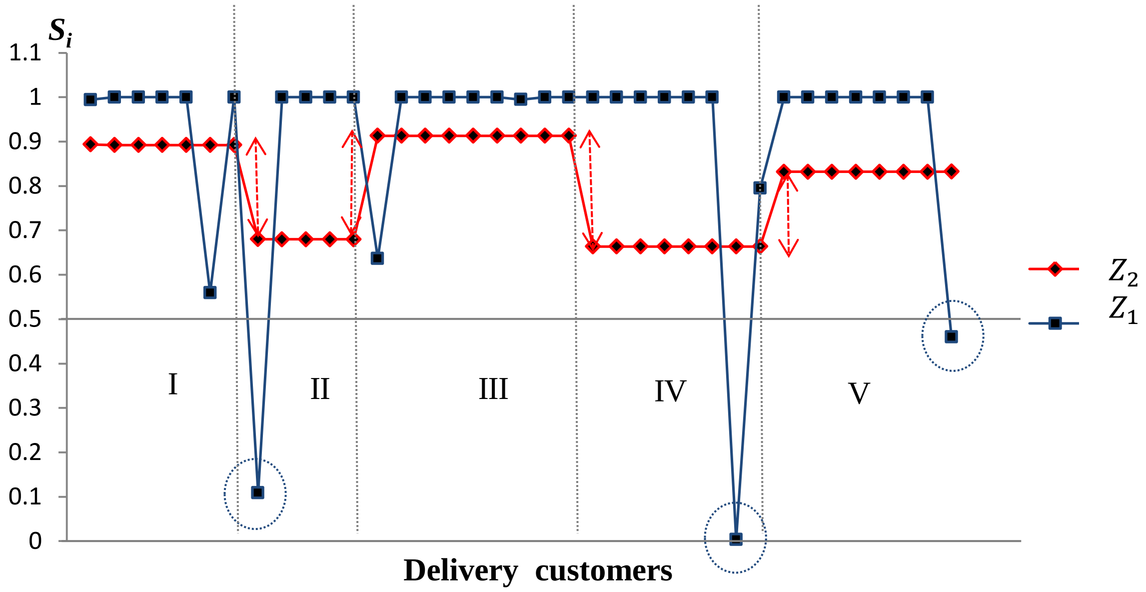

FIGURE 4 Satisfaction of Delivery Customers.

Figure 4 represents the satisfaction of the delivery customers obtained under objective function Z_1 and Z_2. While Z_1 maximizes the total satisfaction of delivery customers, the S_i value of the highest and least satisfied customer is 1 and 0 that leads to an inequality in the distribution of rescued food. The historical data obtained from OzHarvest shows that value of the highest and least satisfied customer varies from 1 to 0.39, which also represents inequitable distribution. On the other hand under the objective Z_2, in each region the S_i values of customers are almost equal leading to an improved equitable distribution of rescued food. Table 4 presents the optimal solution obtained in each region. Gray shaded columns represent the optimal solutions obtained for Z_0, Z_1 and Z_2. Although Z_2 minimizes the total transportation cost, it leads to inequitable distribution and wastage of food. Objectives Z_1 and Z_2 minimizes the waste along with maximizing satisfaction. Since the network is divided into 5 regions and the VRP is solved for each region separately, the satisfaction of delivery customers varies from region to region even under equity objective Z_2.

TABLE 4 Optimal Solutions – Case Study

Region	Objective function					
	Z_0 (km)- wastage			Z_0 (Km)	Z_1	Z_2
I	57.14	13kg	Z_1	63.17	6.55	0.56
			Z_2	61.90	6.25	0.89
II	27.9	0	Z_1	50.43	4.11	0.11
			Z_2	33.4	3.40	0.68
III	129.72	66kg	Z_1	144.5	8.63	0.64
			Z_2	188.42	8.22	0.91
IV	75.2	10kg	Z_1	110.9	6.80	0.00
			Z_2	87.09	5.31	0.66
V	140.45	0	Z_1	165.8	7.46	0.46
			Z_2	149.15	6.66	0.83

Comparing the equity objective Z_2 with Z_1 and Z_0.			
Region	Improvement in S_i of least satisfied customer	% increase in total transportation cost(distance) compared to optimal Z_0	% decrease in total satisfaction of system compared to optimal Z_1
I	0.33	8.33	4.8
II	0.57	19.71	20.88
III	0.27	45.54	4.98
IV	0.66	15.81	28.06
V	0.37	6.19	12.01

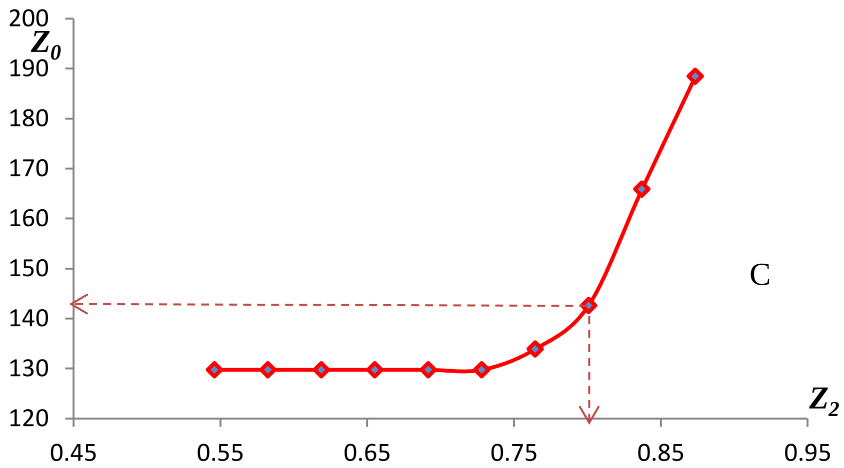

FIGURE 5 Trade-off curve- OzHarvest Case Study.

Table 4 also presents the comparative analysis of optimal solution of Z_2 with Z_0 and Z_1. While an equitable distribution of rescued food can be attained in region I, II, IV and V with less than 20 % increase transportation cost, in region III optimal Z_2 can be attained only at an expense of 45% of transportation cost. In such cases a bi-objective model discussed in section 4.2 can be used to find a trade-off between equity and transportation cost. Figure 5 presents the trade-off between cost objective Z_0 and the equity objective Z_2. Point C can be selected based on the preference and requirements of food delivery operations. At point C the Z_2 Value can be improved to 0.8 with a 10 % increase in transportation cost

5 CONCLUSIONS AND FUTURE DIRECTIONS

In this paper, we address the food delivery policies in the food relief problem. We studied the impact of two critical objectives: maximization of the total satisfaction and the maximization of equity in the distribution of rescued food in food relief operations. We found that there is a significant difference in solutions that focus on the effective and equitable allocation of rescued food with minimum wastage and the solutions that focus on the traditional routing cost minimization. The cost minimizing approach (Z_0) focuses only on efficient routing, and leads to less satisfaction of customers and inequitable distribution of rescued food. Although Z_1 and Z_2 aims at maximizing equity and satisfaction, the two different objective functions leads to difference in route structure and satisfaction of agencies. A comparative study is performed using instances created from the benchmark instance proposed by Breedam and instance representative of OzHarvest operations. Among the objectives studied max-min is more consistent with the goals of food rescue and delivery operations. A sensitivity analysis study is performed to better understand the nature of the problem and behavior of the solution

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relative to variation in the number of vehicles. Although the results show that the optimal solutions are sensitive towards the number of vehicles used, we cannot generalize that the optimal solution improves with an increase in the number of vehicles. Two bi-objective vehicle routing models are proposed extending the classic cost minimizing problem incorporating equity objectives. The ability of models to enhance the equitable distribution of rescued food without losing sight of minimizing transportation cost is discussed and compared. We also discuss the significance of bi-objective models in food rescue operations through a case study. One of the limitations of the paper is a testing and analysis of the model using small instances. Hence, future research will be focused on developing a heuristic approach to solve bigger instances. Our model is suitable only for an equitable allocation of total food rescued or an equitable allocation of a single priority commodity. Hence another extension would be to consider the problem with multiple commodities providing appropriate weightage to each commodity. We also aim at incorporating uncertainty in supply in routing models which is more challenging.

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