Redesigning Mid-day meal logistics of Akshaya Patra Foundation: OR at work in feeding hungry school children

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Abstract

Mid-day meal schemes at schools are prevalent in countries such as India. They help improve the enrolment, retention and participation of children at school. The Akshaya Patra foundation, a not-for-profit organization operates such a scheme for about 1.3 million children in over 9000 schools across 9 states of India. They faced the logistics problem of efficiently distributing the food within the available time-window. This paper discusses the challenges faced and how they were overcome during OR modeling, design, development and implementation of a software solution. A three-stage decomposition heuristic solution was proposed to address the logistics problem. This consists of clustering of schools, assignment of appropriate vehicles to clusters, and routing within the clusters. A software version of the solution (AMRUTA) was implemented on a pilot basis in one of the locations.

The projected annual cost savings from this pilot implementation is US$75,000, which will enable them to add 2,400 more children every month. Once fully implemented the estimated cost savings is about US$1.96 million. The solution approach proposed in this paper has application potential in similar capacitated vehicle routing problems with time windows especially in the distribution of food/beverages. This paper demonstrates the potential for application of OR/MS principles to address several unmet needs pertaining to societal welfare maximization.

Key words: Distribution Logistics, OR/MS Implementation, Heuristics, Case Study, Software Implementation

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Introduction

Mid-day meal schemes (MDMS) at schools are prevalent in countries such as India. MDMS is a mechanism to address the socio-economic objectives of boosting enrolment, retention, participation and nutritional status of children at schools. An efficient MDMS program can therefore play a significant role in welfare maximization of the society and go a long way in improving the standard of living. As of 2010, the Indian MDMS program is the largest of its kind covering about 100 million children (Right-to-Food-India, 2010) with close to two-third of the beneficiaries based in rural India (Ghatak S. , 2010). The program is administered in a decentralized manner by various public & private operators. The desired scale of coverage and the inadequacy of storage/connectivity infrastructure in rural areas pose a distribution challenge to all incumbent MDMS operators.

The Akshaya Patra foundation (TAPF) is a not-for-profit organization that operates MDMS for about 1.3 million children in over 9000 schools across 9 states of India. The vision of TAPF is *"No child in India shall be deprived of education because of hunger"*. TAPF activities have gone up significantly over the last 9 years. From 23,000 children in 2003, TAPF delivers lunch to nearly 1.3 million children in 2012. The demand is continuously growing and they aspire to reach 5 million children by 2020. While the growth has greatly helped TAPF approach their vision it has also introduced operational challenges.

Their operating model involves centralized kitchens where hot food is cooked. The cooked food from a kitchen needs to be distributed daily to about 600 schools in the surrounding areas. The maximum available time window for "cooking to consumption" is about 6 hours. The cooking capacity installed, processes adopted, and technology deployed required a major overhaul on account of the increased scale of operations. TAPF has consequently installed the state-of-the-art cooking technology in all their 19 kitchens. Another area of great concern was the mounting complexity of the logistics/distribution of the cooked food. As more schools were added to the network, new clusters of schools were created on an incremental basis. Also their current distribution model was not able to handle variations in traffic & road conditions. This led to delays in delivery of food at schools, forcing children to skip lunch and thereby challenging its very objective.

On another front, due to increased scale of operations at the kitchens, the marginal cost of adding a new demand point was low compared to the marginal cost of distribution. Thus distribution became a critical bottleneck for TAPF in their attempt to improve efficiency of operations and increase the coverage. As of 2010, the kitchen at Vasanthapura in South Bangalore delivered food to about 530 schools using a fleet of 35 vehicles. The senior management at TAPF felt that there was scope to service the existing demand with fewer vehicles provided the logistics planning was better; *using the released capacity they could potentially serve additional children*. Since TAPF did not have a formal method of logistics planning, nor a computer based algorithm to address this issue, an opportunity for improvement was identified.

The logistics problem faced by TAPF was to find an efficient solution that minimizes the utilized fleet capacity while meeting the time-windows requirements. This logistic problem belongs to the general class of vehicle routing problems called the Heterogeneous Fixed Fleet Vehicle Routing Problem with Time windows (HFFVRPTW). This problem is a more challenging version of an earlier work titled "Meals on Wheels"(Bartholdi III, Platzman, Collins, & Warden III, 1983).

The software solution called AMRUTA (**A**khaya Patra **M**id-day meal **R**o**U**ting and **T**ransportation **A**lgorithm) was pilot deployed at Vasanthapura (Bangalore South) kitchen of TAPF (see figure 1 for the opening screen of AMRUTA). AMRUTA has reported promising savings both in terms of monthly operating cost and the number of delivery vans. The projected annual cost savings from this pilot implementation is US$75,000 (18.61% of the monthly operating cost), which will enable them to add 2,400 more children. Once fully implemented in all the other kitchens, the estimated cost savings is about US$1.96 million. This will enable TAPF to increase expand their services nationally by an additional 62,000 children at prevailing costs. Therefore, this solution offers great promise to take TAPF closer to their vision of reaching more poor students.

The three-stage decomposition heuristic solution implemented in AMRUTA consists of clustering of schools, assignment of appropriate vehicles to clusters, and routing within the clusters. In the first stage the capacitated clustering problem is solved using a modified K-means clustering algorithm. The fleet assignment to clusters is done using a greedy-heuristic followed by 2-opt interchanges and the intra-cluster routing optimization problem solved using a Self-Organizing Map (SOM) genetic algorithm.

This paper addresses the TAPF problem by demonstrating the power and usage of OR tools and techniques coupled with user-friendly computer software. The model development, implementation and the results reinforce the power of OR/MS to address unmet problems social problems pertaining to societal welfare maximization. Furthermore, the solution model and the software developed are capable of addressing similar capacitated distribution problems with time window constraints especially in the food & beverages industry. The research contribution in this paper is the modeling & development of the heuristic solution and adaptations made for practical implementation of solving industrial-grade logistics problem.

Mid-day Meal Logistics

TAPF owns 19 kitchens spread across 9 states of India, with cooking capacities in the range of 50,000 to 185,000 meals a day. We will refer to the case of Vasanthapura (Bangalore south) as an example to illustrate the scale of their distribution problem. Vasanthapura kitchen has a cooking capacity of 50,000 meals a day. Cooking is done using mechanized steam-heated cauldrons that are custom-built to mass-produce for the required scale. The typical cooking process starts at 4 AM and the first batch of cooked food is usually available around 7 AM. The cooked food needs to be delivered at schools before 1 PM allowing a total transportation window of four to six hours. The food is packed in stainless steel containers for transportation. The food menu consists of three food items, cooked rice, Sambar (Lentil soup), and curd (Yoghurt) which are loaded in large, medium and small size containers respectively.

Vasanthapura currently has a fleet of 35 delivery vans of varying capacities. These delivery vans have a three-tier rack structure suitable for loading the three custom-sized containers. The staffing pattern for each delivery-van includes a *driver, a supervisor, and one or two load-unload personnel* to deliver the service. Vasanthapura location currently services about 530 schools. The daily demand at each school is fairly stable in contrast to the “meals on wheels” problem (Bartholdi III, Platzman, Collins, & Warden III, 1983). There is ample demand to increase the service coverage, but TAPF are constrained by the fleet capacity and the available time-window.

The capital investment for acquisition of a delivery van is about US$28,000. The acquisition decision is annually made at the central office of TAPF and is beyond the operating budget of individual regions (locations). The regions are annually assigned a limited fleet of delivery vans by the central office and only the operating costs are managed at the regional level. The objective of the Manager in each region is to make the best use of the available resources to maximize the service coverage. The average cost to cook a meal is Rs. 5 (ten US cents) with 2/3rd of the cost being subsidized by the government. An additional 20% overhead is incurred towards distribution and is borne by the MDMS operators. In addition, TAPF incurs additional costs for monthly maintenance of the delivery vans and towards staff salaries.

The total daily trip length of Vasanthapura region as per their existing routing was about 1400 kilometers. The fuel cost, vehicle maintenance cost, and staff salaries are the main components of the distribution cost. The expectation of the regional management team of TAPF was to reduce their monthly distribution cost and utilize the savings towards improving their service coverage. More details on the operating model of TAPF are available in the website of TAPF (TAPF, 2012) and the case study on TAPF published by Harvard Business School (Upton, Ellis, Lucas, & Yamner, 2007).

AMRUTA: OR modeling, Solution and Software Design

Operations Research Model

There is abundance of OR literature available on vehicle routing problem (VRP) variants that somewhat resemble the TAPF problem. Dell'Amico, et al (Heuristic approaches for the fleet size and mix vehicle routing problem with time windows, 2007) and Braysy, et al. (An effective multirestart deterministic annealing metaheuristic for the fleet size and mix vehicle-routing problem with time windows, 2008) studied the Fleet size mix Vehicle routing problem with time windows, which resembles the TAPF problem. In their problem variant, the optimal fleet size and mix is endogenously determined from a heterogeneous catalogue of available vehicles along with the best routing solution. However, in our problem the choice of number of vehicles and vehicle types is strictly limited to the fixed fleet available within each location. Tarantilis, et al. (A list based threshold accepting metaheuristic for the heterogeneous fixed fleet vehicle routing problem, 2003) and Li, et al. (A record-to-record travel algorithm for solving the heterogeneous fleet vehicle routing problem, 2007) studied the Fixed fleet Heterogeneous Vehicle routing problem, which also resembles the TAPF problem. However the TAPF problem is additionally constrained on time windows. Privé, et al. (Solving a vehicle-routing problem arising in soft-drink distribution, 2005) discussed a practical case of a distribution problem of a soft-drink manufacturer involving a heterogeneous fleet in a capacitated environment with time windows. Unlike the situation described in their paper, TAPF need not plan for the return logistics of recycled material. Instead TAPF faces the constraint of a fixed fleet size. Overall the TAPF case can be generalized as a case for Heterogeneous Fixed Fleet Vehicle Routing Problem with Time

Windows (HFFVRPTW). The Mixed Integer formulation of the TAPF problem is given in Appendix-A.

Solution Approach

Development of solutions for industrial grade transportation problems involving large number of nodes typically requires a combination of heuristics and multi-sage decomposition (Fisher & Jaikumar, 1981) (Thangiah, Osman, & Sun, 1994) and (Tan, Lee, Zhu, & Ou, 2001). The solution approach adopted for AMRUTA was along the similar lines. Dondo & Cerdá (A cluster-based optimization approach for the multi-depot heterogeneous fleet vehicle routing problem with time windows, 2007) studied the heterogeneous fleet capacitated vehicle routing problem with time windows in the context of multiple depots. They proposed a three stage solution approach where the cluster of nodes around the depots were determined in the first stage, the assignment of vehicles to clusters was done in the second, and the ordering of nodes within the clusters was determined in the third stage. The proposed solution approach for AMRUTA is similar.

The solution approach can be decomposed to three stages:-

(1) Stage-1 : Creating *k*-clusters of demand Nodes

(2) Stage-2: Assignment of *k*-vehicles to the k-clusters

(3) Stage-3: Ordering of nodes within the clusters

The solution techniques proposed for the respective stages are:-

(1) Stage-1 : Modified version of *K*-means clustering

(2) Stage-2: A greedy heuristic initial solution followed by a series of 2-opt interchanges

(3) Stage-3 : A self-organizing map (SOM) based genetic algorithm heuristic

The schematic model of the proposed solution approach of AMRUTA is given in Figure 2.

Stage-1

The objective of the first stage is to create *k*-clusters that minimize the intra-cluster travel distance for vehicles. This reduces to a Capacitated Clustering Problem (CCP). In this problem *n*-nodes are to be clustered into *k*-clusters with the objective of minimizing route cost/distance within a specified cluster capacity constraint. CCP is typically solved using the K-means clustering algorithm. K-means is a simple and computationally efficient method for partitioning a set of points with the objective of minimizing their distance to the Centroid. The quality of solutions generated by the *K*-means clustering algorithm is usually dependent on the quality of the choice of initial seeds (or initial centroids). Several approaches are available for solving this problem (Krishna & Narasimha Murty, 1999), (Lu, Lu, Fotouhi, Deng, & Brown, 2004), (Zalik, 2008), (Geetha, G., & Vanathi, 2009).

The solution technique in AMRUTA is similar to Geetha, et al (Improved K-Means Algorithm for Capacitated Clustering Problem, 2009). In this approach the top *k*-large demand nodes are chosen as the initial centroids. Then the remaining nodes are clustered based on their priority values; lower value indicating higher priority and vice versa. The priority value of a node is calculated as the ratio of its distance to the cluster centroids and the demand at the node. An unassigned node is assigned to the nearest cluster having adequate capacity to serve the demand at the node. The time-window consideration is relaxed during this stage. This partitioning logic ensures that large demand points are kept separate as much as possible, so that the smaller demand points can be packed into nearest clusters without violating the capacity constraints.

Stage-2

At this stage vehicles are assigned to the clusters without violating the capacity and time-window constraints. After the initial allocation of vehicles to the clusters is completed, the cluster membership can be improved. Several studies utilize a similar approach (Thangiah, Osman, & Sun, 1994) (Tan, Lee, Zhu, & Ou, 2001) (Ferland & Michelon, 1988). Tarantilis, et al. (A list based threshold accepting metaheuristic for the heterogeneous fixed fleet vehicle routing problem, 2003) proposed an algorithm to a VRP problem which is similar to the Stage-2 of the TAPF problem. They improve the initial vehicle assignment solution using a local search technique called LBTA which involves a series of 2-opt moves of arcs between routes to improve the objective function without violating the capacity constraint. The solution technique proposed in AMRUTA is similar to this paper, but with the additional consideration of time windows. AMRUTA initially follows a greedy heuristic where the first *k*-vehicles from the fixed fleet with adequate capacity and the lowest monthly operating cost are initially assigned to the *k*-clusters. The quality of the generated solution is subsequently improved by carrying out a series of 2-Opt moves between clusters with the objective of reducing the monthly operating cost. The heuristic ensures that the constraints of capacities and time windows are not violated. This process leads to merger and de-merger of clusters, finally yielding the best solution that minimizes the monthly operating cost.

Stage-3

In the third stage a route planning heuristic is used to arrive at the visitation sequence of the nodes in each cluster. This problem resembles the familiar travelling salesman problem (TSP) for each of the *k*-petals of the overall route map. But the constraints on capacities and time windows still need to be preserved in the final solution. The TSP problem is a well researched topic in OR literature. Refer (Laporte, Louveaux, & Van Hamme, 2002) and (Nilsson, 2003) for a survey of exact and approximate solution techniques available for the TSP problem. Gendreau, et al. (Metaheuristics for the capacitated VRP, 2002) provide a good overview of application of meta-heuristics to capacitated VRP. Self organizing map (SOM) is a genetic algorithm useful for solving industrial-grade TSP problems. The SOM algorithm was first proposed by Kohonen (The self-organizing map, 1990). Several studies discuss the application of SOM algorithm for solving the TSP and VRP problems (Budinich, 1996), (Modares, Somhom, & Enkawa, 1999) (Bai, Zhang, & Jin, 2006), (Brocki & Korvzinek, 2007) and (Créput, Koukam, & Hajjam, 2007).

The SOM algorithm is computationally efficient and generates high-quality heuristic solutions. The basic idea of SOM is that in a single dimensional TSP problem, the greedy nearest neighbor heuristic of jumping to the next unvisited node generates good quality solutions. SOM extends this concept by projecting points from 2-dimensional Euclidean space onto a circular ring and applies the nearest neighbour principle on the projected images. Since perfect preservation of neighborhood is not possible with projection, the genetic algorithm needs clever choices of policy parameters to preserve the neighborhood as much as possible. The SOM algorithm needs two policy parameters viz. the learning rate α and the neighborhood function variance σ. In AMRUTA the choice of these parameters are made in line with the recommendations by Bai, et al. (An new self-organizing maps strategy for solving the traveling salesman problem, 2006).

AMRUTA Implementation

Software Design Considerations

The design and development of the algorithm and the software were based on four key considerations: meeting management expectations, end-user acceptance, low cost and ease of maintenance. The management preferred a range of best solutions for the available fleet over a single solution. The expectation was to use this range of solutions to determine the best “trip-sheet” for the day considering factors such as staff absenteeism and vehicle unavailability. They also preferred a graphical representation of the solution and needed multiple MIS reports. Figure 3 has the plot of the routing pattern (35 vehicles) prior to the implementation of the model and Figure 4 has the solution generated by AMRUTA with 27 vehicles. The graphical representation of the solution improves transparency in its working and generates confidence among the users.

Annually after a summer break the schools in India reopen in June. This period also coincides with the annual planning and capacity augmentation cycle of TAPF. During this time TAPF management considers requests for including more schools into the distribution network. Therefore annually information on fleet availability, number of schools to be served and the demand at each school get modified. Moreover, from time to time certain other model parameters *(such as cost parameters)* need to be modified. Therefore, ease of data input, maintenance and execution of the algorithm were the other considerations. Finally, another important consideration in software design was the user acceptance pertaining to the software. Since the user-base of TAPF was not technologically savvy, ease of use was an important consideration. TAPF also cannot afford expensive licensed software and upgrade costs. Therefore, low license cost, usability and ease of maintenance were the other considerations.

Software Implementation

With these design considerations in mind, the software solution AMRUTA was developed using Microsoft Excel and Visual Basic. Since the software was a part of the standard desktop configuration of TAPF, every user had access and some prior experience with usage. Additionally the ease of data maintenance with a spreadsheet and the graphical reporting features available in Microsoft Excel made it a suitable candidate. Figure 5 has a snap shot of the input data pertaining to the demand points and fleet size. The data on the geographical distribution of the demand nodes was represented using the GPS coordinates of the schools. Use of spreadsheet improves ease of installation, data maintenance and user acceptance.

The output from AMRUTA consists of a Master solution summary which gives an overview of the range of solutions that were generated including their trip elapsed times, trip distances and total operating costs (refer Table 1). AMRUTA also generates a series of solution-level output reports for each of the solutions. Some of the output reports for a candidate solution include the solution summary (refer Table 2) and the graphical route map (refer Figure 4). The software also generates a Trip sheet *(in both tabular format and graphical view)* for each route identified in the solution (refer Figure 6).

The master solution summary is a MIS type report used by the regional operations management team of TAPF to decide on the best daily routing plan. It also helps them make dynamic decisions on the best routing alternative for the day, considering staff absenteeism and vehicle unavailability. The solution summary report is used to get a drilled-down view of the routing plan and the cost. This report is used by the TAPF operations managers to subsequently compare against the actual expenses incurred in a trip. The trip-sheet generated by AMRUTA is printed and handed over to the driver/supervisor for the vehicle as an aid for their travel. Comparison of the generated trip sheet and the actual trip data could be used to improve the policy parameters for executing AMRUTA. These reports were useful during user-acceptance testing and pilot implementation for critically reviewing the working of the algorithm and fine-tuning of policy parameters. These reports help the management estimate the potential savings generated by AMRUTA.

The processing time for AMRUTA on a standard Windows desktop is about 3 minutes. The complete set of report generation takes an additional 10 minutes. These processing times are consistent with the requirement of the TAPF management team to frequently re-execute the software in the event of changes to the input data.

AMRUTA was pilot implemented in Vasanthapura (Bangalore South) region during March – August 2011. After the implementation, the number of delivery vans used was reduced from 35 to 27. The annualized cost savings realized in this region during the pilot period was US$ 75,000 (18% savings in monthly operating cost). This amount would enable them increase their service coverage by about 4.8% or an additional 2,400 children. The solution is also eco-friendly because it reduces the total trip length for the region from 1400 Km to 1325 km thereby saving about 443 litres of diesel per month. Currently AMRUTA is being implemented in all other kitchens of TAPF. Assuming cost savings of similar proportions, the projected annual savings across India is expected to be in the range of US$ 1.96 million. This will enable them to expand their services nationally by an additional 62,000 children at the prevailing costs.

Adaptations for Implementation

Given the scale of the TAPF logistics problem, AMRUTA needed several heuristic adjustments and adaptations to the standard OR algorithms. These were required both for improving the simplicity in formulation and the mathematical tractability of the solution. When using heuristics to solve large real life problems the user acceptance and the quality of the solution critically depends on the manner in which realistic conditions are abstracted in the model. Care needs to be taken that these abstractions do not compromise the solution quality or overly increase the complexity of the algorithm. We had to address these issues during the development of AMRUTA.

To improve processing time and mathematical tractability, the demand for the food items was converted into aggregate demand units. Similarly a correction factor was applied to the Euclidean distance calculated to account for actual road and traffic conditions and available connectivity between the nodes. Furthermore, the model uses two speed bands i.e. one for the travel between the kitchen and the first node in the cluster and the other for travel between successive nodes within the cluster. This adjustment helped account for the variation in vehicle speed between urban and rural roads and the frequent stop – start sequence within the cluster. The service time at a school was split into a fixed component and a variable component linked to the number of containers to be unloaded at the site.

Similarly in the three-stage decomposition structure, the first stage of clustering only checks for violation of the capacity constraint and the check on time windows was relaxed. To accommodate this relaxation, the clusters are loaded only up to 80% of the capacity. But during the stage-2 when the clusters get merged & de-merged during the 2-Opt interchange, the inefficient clusters get eliminated. Of the total time available, the transportation and service time are assumed to be split in a 60-40 ratio. This assumption means if 240 minutes is available for a trip, nodes are added only until a total travel time of 144 minutes. After the initial solution is created, the approximation is removed and actual service times are used for fine tuning the solution. These adjustments helped improve the processing time and tractability of the solution.

All these heuristic adjustment factors were modeled as input parameters to AMRUTA. Since the quality of solution is a function of input data, such a parametric design approach provides the ability to continuously review and fine-tune these parameters during pilot implementation and on an ongoing basis in the future as well. This approach facilitated smoother user acceptance of the proposed solution.

The choice of providing a range of solutions rather than a single "take it or leave it" solution was a critical decision. Such an approach provides a greater understanding of the behavior of various cost structures and helps the management gravitate towards a *"workable solution"* that satisfies the overall requirement. It also provides an opportunity for the management and the users to actively participate in the decision making. Multiple solutions for various fleet sizes enabled them to understand the critical tradeoff between cost and responsiveness. For example, if the number of number of vehicles were reduced from 27 to 26, the average trip elapsed time increased by 8 minutes and the average distance per vehicle by 2.73 km. The total distance covered increased by 22 Km but the operating cost reduced by about US$ 800 per month; net of the savings from the dropped vehicle and increase in the travel cost. Moreover, generating a range of solutions offered flexibility to handle staff absenteeism and vehicle unavailability. The idea of easy-to-maintain spreadsheet format inputs and the usage of graphical features to represent the solution output, helped critically validate the results during user acceptance and implementation. Similarly inclusion of MIS reports improved transparency of the working of the algorithm. Overall these solution design aspects helped improve the confidence and up-take of the solution among the user community.

Conclusion

Mid-day meal schemes at schools are prevalent in countries such as India. They are aimed at improving the enrolment, retention and participation of children at school. The Akshya Patra Foundation faced the problem of using a fixed fleet of vehicles to efficiently distribute the food within the available time-window. This paper discusses the challenges faced and how they were overcome during OR modeling, design, development and implementation of software solution. The results from the pilot implementation show significant promise in aiding TAPF to get closer to their vision of *not letting a child go hungry at school.*

The heuristic solution approach discussed in this paper would be of interest to researchers and practitioners working on large-scale capacitated vehicle routing problems with time window constraints. This HFFVRPTW problem discussed in this paper is representative of the logistic problem involved with distribution of perishable food & beverages. Therefore, the model could serve as a case study for practical application of OR algorithms in the distribution problems faced by food & beverages industry. It can also be extended to other industries that face similar constraints of fixed fleet capacity and strict time-windows.

Better solution algorithms *especially* those based on adaptive learning techniques can further improve the quality of solutions generated by AMRUTA. Consideration of stochastic demand and service times is an area of extension for further research. Integrated distribution planning of all the kitchens in a multi-depot distribution model is another such extension. The TAPF vision *"No Child should be deprived of education due to hunger*" is a significant dimension to social welfare and societal transformation in countries like India. This case illustrates the potential for application of OR/MS Algorithms and implementations to address such serious real-world issues.

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Appendix – A: Mathematical Formulation of the TAPF Problem

The Mixed Integer formulation of the TAPF problem is given below in the notations used in the MIP formulation of the FSMVRPTW problem proposed by (Braysy, Dullaert, Hasle, Mester, & Gendreau, 2008) for ease of cross-referencing.

Let C be a set of all the customer demand nodes. Let Node 0 signify the central kitchen from where the transportation happens. We define N as the set union $\{0\} \cup C$. Let K be the set of vehicle types. Factors like capacity limit and mileage offered are specific to the vehicle type. Let L_k be the set of individual vehicles available within each type of the fixed fleet *k*.

The definitions of the variables used in the formulation are as follows:-

- X_{ij}^{kl} ➔ An Indicator variable that is set to 1, if the vehicle of type k with vehicle number l, directly travels from node-*i* to node-*j* in the undirected graph.
- Y_i^{kl} ➔ A Non-negative Real number that captures the arrival time of vehicle of type-*k* with vehicle number *l*, at node-*i*.

The definitions of the constants used in the formulation are as follows:-

- d_i ➔ Equivalent demand of food at node-*i* ; It is a composite demand of the 3 food items in an equivalent scale.
- q_k ➔ Capacity limit of vehicle of type-*k* expressed in equivalent demand units.
- s_i ➔ Service time at node-*i*; This can contain a fixed component and a variable component per container.
- t_{ij} ➔ Vehicle independent travel time between node-*i* and node-*j* .
- a_i ➔ Earliest acceptable arrival time at node-*i*.

- b_i ➔ Latest acceptable arrival time at node-*i*.
- M_{ij} ➔ A large Integer M which acts as an upper-bound; According to (Braysy, Dullaert, Hasle, Mester, & Gendreau, 2008) we can set the bound for this term as max($b_i + s_i + t_{ij} - a_j$, 0) $\forall$ i $\in$ N, $\forall$ j $\in$ N, $\forall$ k $\in$ V , $\forall$ l $\in$ L_k.
- C_{ij}^k ➔ Travel Cost for transportation between node-*i* and node-*j* using a vehicle of type-*k*; It is a function of t_{ij} and the mileage offered by vehicle of type-*k*.
- MC^k ➔ Monthly Operating Cost of Vehicle of type-*k*; it includes the vehicle maintenance cost and staff salaries of people manning the vehicle.

$$\text{Min} \sum_{k\in V}\sum_{l\in L_k}\sum_{j\in N}\sum_{i\in N} C_{ij}^k * x_{ij}^{kl} + \sum_{k\in V}\sum_{l\in L_k}\sum_{j\in C} MC^k * x_{0j}^{kl}$$

Subject to

$$\sum_{k\in V}\sum_{l\in L_k}\sum_{j\in N} x_{ij}^{kl} = 1 \quad \forall\, i \in C \qquad (1)$$

$$\sum_{i\in C} d_i * \sum_{j\in N} x_{Ij}^{kl} \le q_k \quad \forall\, k \in V \qquad (2)$$

$$\sum_{j\in N} x_{0j}^{kl} = 1 \quad \forall\, k \in V, \forall\, l \in L_k \qquad (3)$$

$$\sum_{i\in N} x_{ih}^{kl} - \sum_{j\in N} x_{hj}^{kl} = 0 \quad \forall\, h \in C, \forall\, k \in V, \forall\, l \in L_k \qquad (4)$$

$$\sum_{i\in N} x_{i0}^{kl} = 1 \quad \forall\, k \in V, \forall\, l \in L_k \qquad (5)$$

$$y_i^{kl} + s_i + t_{ij} - y_j^{kl} \leq (1 - x_{ij}^{kl}) M_{ij} \qquad (6)$$

$$a_i \sum_{j \in N} x_{ij}^{kl} \leq y_i^{kl} \ \forall i \in N, \forall k \in V, l \in L_k \qquad (7)$$

$$b_i \sum_{j \in N} x_{ij}^{kl} \geq y_i^{kl} \ \forall i \in N, \forall k \in V, \forall l \in L_k \qquad (8)$$

$$x_{ii}^{kl} = 0 \ \forall i \in N, \forall k \in V, \forall l \in L_k \qquad (9)$$

$$x_{ij}^{kl} \in \{ 0, 1 \}$$

$$y_i^{kl} \in \vec{\boldsymbol{R}} \ ; y_i^{kl} \geq 0$$

The objective function attempts to minimize the sum of the transportation cost and the monthly operating cost of the fixed fleet. Constraint (1) ensures that every node is visited exactly once and by only one vehicle. Constraint (2) is the heterogeneous capacity constraint posed by the vehicle. Constraint (3) ensures that every vehicle is assigned exactly to one route off the kitchen. Constraint (4) is the flow conservation constraint at all intermediate nodes of a route. Constraint (5) ensures that every vehicle ends back at the kitchen exactly once. This also helps in eliminating sub-tours. Constraint (6) preserves the integrity of the arrival times at successive nodes on a route. Constraint (7) and (8) are the constraints on earliest arrival times and latest arrival times. Constraint (9) ensures that invalid arcs are eliminated from consideration.

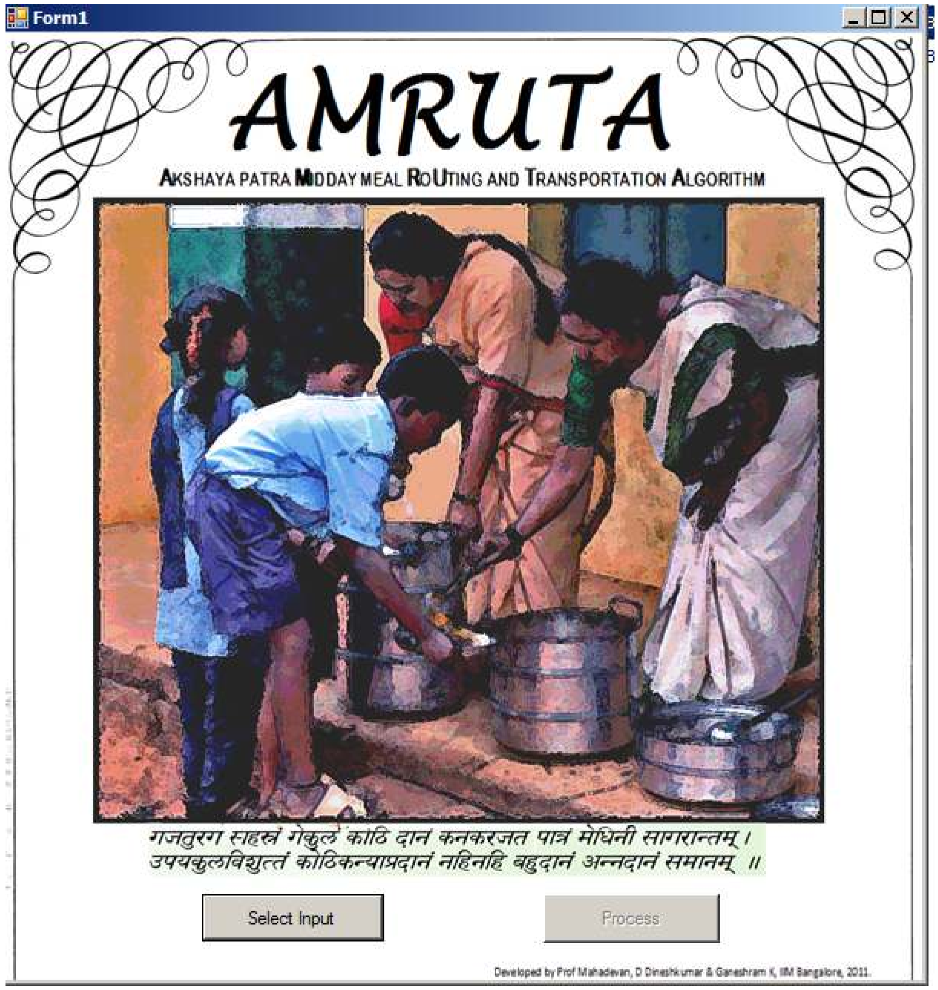

Figure 1: The opening screen of AMRUTA

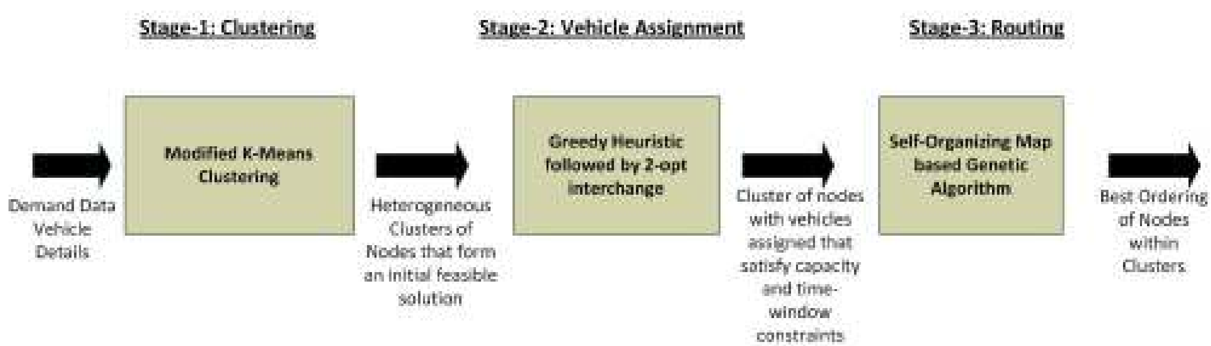

Figure 2: Schematic Model of Solution Approach of AMRUTA

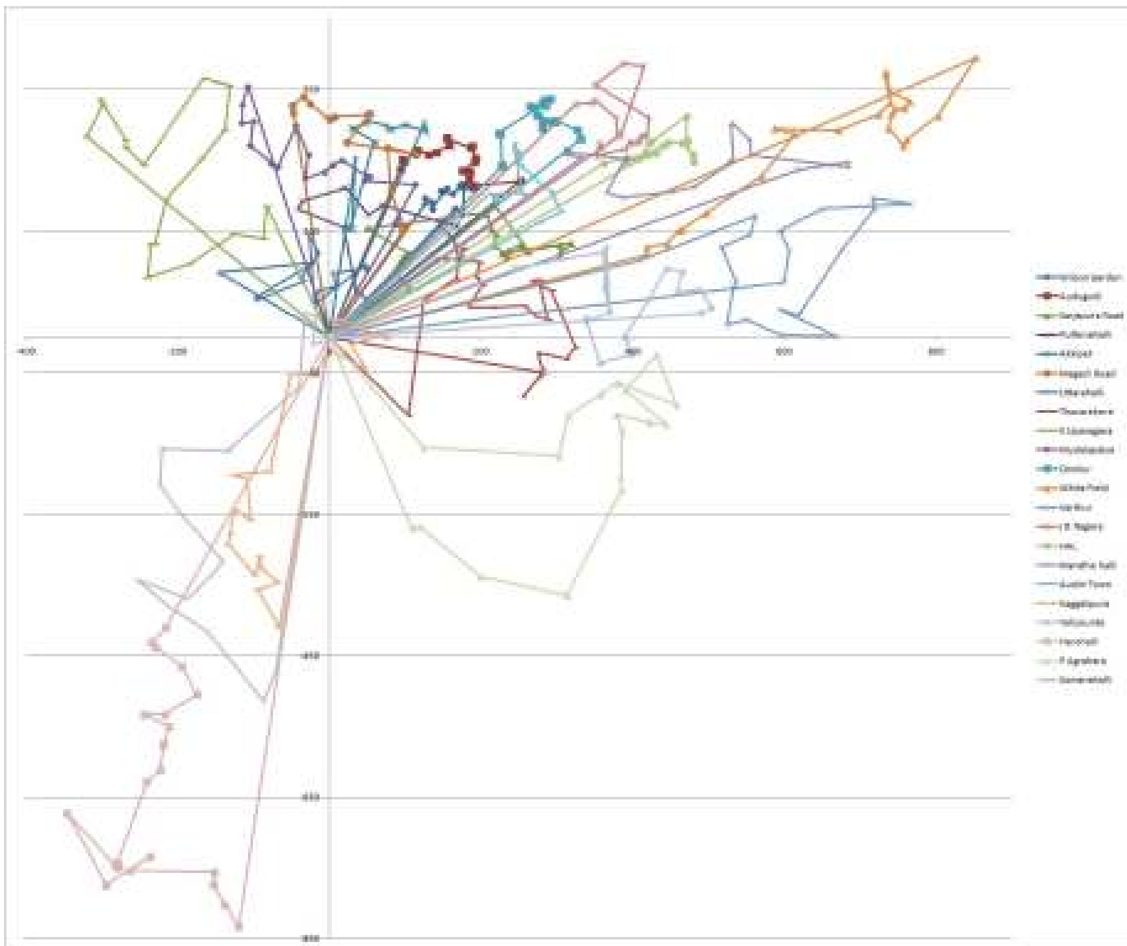

Figure 3: Route Map for Existing model of Distribution of TAPF with crisscrossing routes

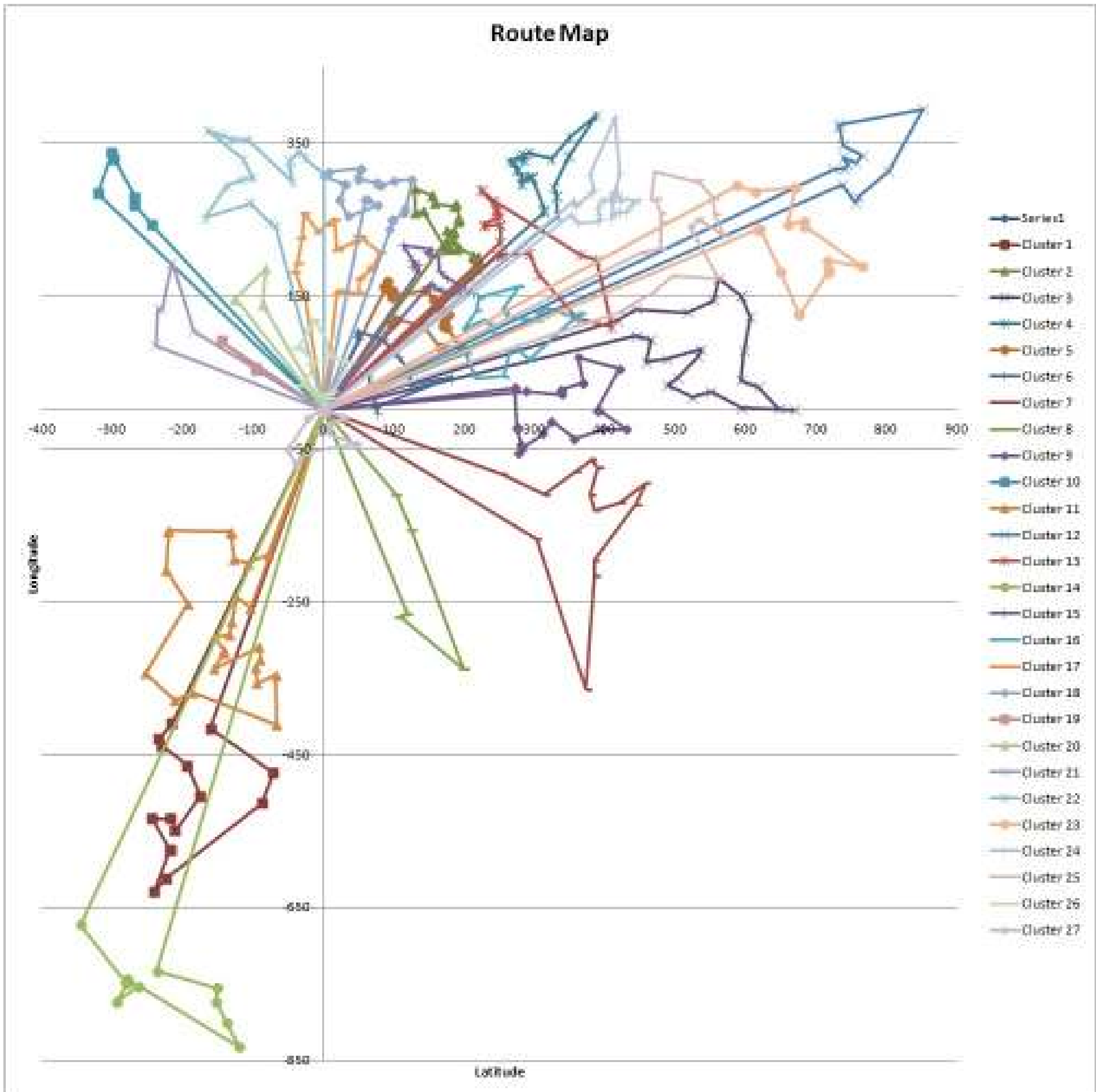

Figure 4: Route map generated by AMRUTA for a fleet of 27 vehicles

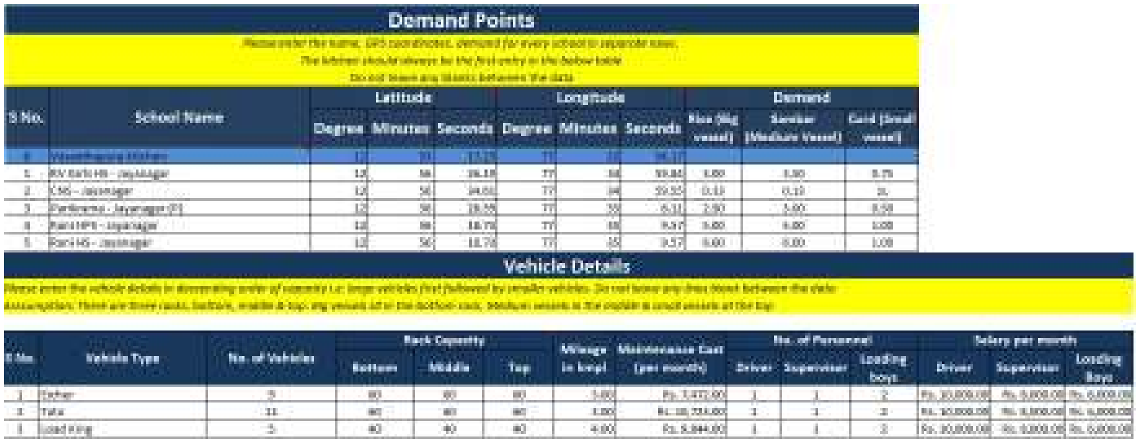

Figure 5: Snapshot of Input data in spreadsheet format to AMRUTA

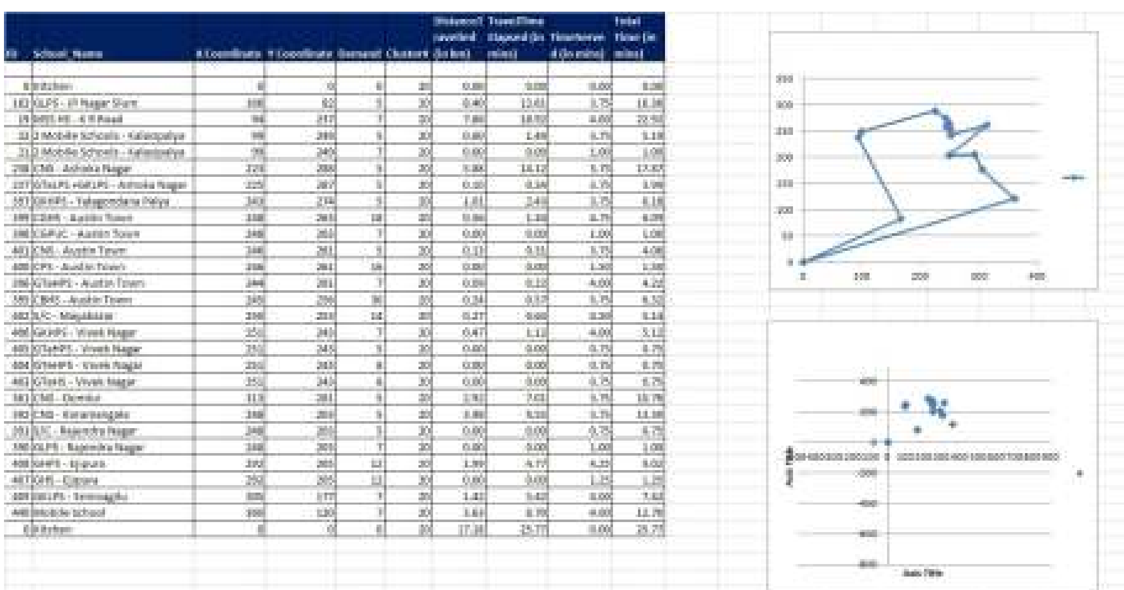

Figure 6: Trip sheet for a single Route with both tabular & graphical representation.

Solution No	No. of vehicles	Elapsed time at the last node (in minutes)			Distance covered (circular) in km			Total Distance covered	Total no. of unclustered nodes	Total operating cost
		Min	Max	Average	Min	Max	Average			
Solution #17	20	125.58	305.73	216.93	35.57	101.96	59.78	1195.69	2	1106840.71
Solution #18	20	119.14	307.53	215.21	28.46	102.71	59.21	1184.17	3	1122372.78
Solution #19	22	126.30	294.00	196.16	28.79	97.29	55.20	1214.32	5	1201722.92
Solution #20	21	119.14	309.55	203.69	26.87	103.55	56.95	1195.97	11	1159595.87

Table 1: Master Solution Summary Output

Cluster #	# of Schools	Total Demand (in Equivalent Units)	Distance Travelled (in km)	Travel Time Elapsed (in Minutes)	Total Non Travel Time (in Minutes)	Total Time (in Minutes)	Unclustered Nodes	VehicleType	Maintenance Cost Per Month (in Rupees)	Employee Cost Per Month (in Rupees)	Travel Cost Per Month (in Rupees)	Total Cost Per Month (in Rupees)
1	15	122	71.98	134.24	57.00	191.24	0	Max Pikup	2825	24000	11876.97	38701.97
2	25	156	40.78	76.34	72.25	148.59	0	Max Pikup	2825	24000	6729.37	33554.37
3	32	326	88.58	176.85	123.75	300.60	1	Tata	10723	30000	29229.96	69952.96
4	32	337	62.41	114.80	120.75	235.55	0	Tata	10723	30000	20595.04	61318.04
5	37	400	46.40	92.86	135.00	227.86	1	Tata	10723	30000	15313.09	56036.09
6	35	352	57.01	129.45	126.50	255.95	0	Tata	10723	30000	18812.07	59535.07
7	18	268	55.30	107.68	72.50	180.18	0	Swaraj Mazda	9844	30000	13686.63	53530.63

Table 2: Solution Summary Output