Efficient Heuristic Methods for Minimizing the Cost of City Bus Operations of Indian Urban Road Transportation Organizations

Rupkatha Ghosh and M. Mathirajan

Department of Management Studies
Indian Institute of Science
Bangalore 560012, India
rupkathag@iisc.ac.in and msdmathi@iisc.ac.in

Abstract

The statistics on financial performances of Indian-Urban Road Transportation Organizations (I-URTOs) indicate that almost every I-URTO is facing huge losses in operating city buses. Considering monetary loss and increased fuel cost, there is a need to address decision problem(s) to minimize the cost of city bus operations (CCBO) without increasing bus fares. These buses traverse many non-revenue generating distances. One such distance is the 'dead kilometers' (DK) which is the summation of the distance traversed from the depot to starting point of first trip and ending point of last trip to the depot without carrying passengers. A report by the Central Institute of Road Transport (CIRT) revealed more than 27 crores DK being incurred in 2016-2017. An efficient allocation of city buses to depots (ACBD) not only reduces DK but also reduces CCBO. The problem of minimizing DK is addressed widely. However, since every bus has a different mileage per unit of fuel, minimizing DK cost (DKC) is more appropriate, which has not been considered in India. Hence, this study considers this issue. Since ACBD can be viewed as a special type of transportation problem, 8 best initial basic feasible solution (IBFS) methods reported in the literature are considered to reduce CCBO. From the performance evaluation, the best-performing method is identified. As this is an ongoing Ph.D. dissertation work, many future research activities like developing and/or including a greater number of IBFS methods, considering depot operating costs/cost due to CO₂ /etc. are in the pipeline as immediate future research issues.

Keywords

Cost of City Bus Operation, Allocation of City Buses to Depots, Dead Kilometer Cost, Heuristic Methods, Computational Experiment, Empirical Performance Evaluation

1. Introduction

Every Indian Urban Road Transportation Organizations (I-URTOs), managed by the respective State Road Transport Undertaking (SRTU), provides public transport services. This is a dominant mode of transport in any urban city to meet the heavy passenger traffic and contribute to the national economy. Further, it is necessary for a country like India as the population is expected to further increase from 121.1 crores to 152.2 crores during 2011-2036 (Census of India), and the majority of them cannot afford private transport. So, people living in the urban cities rely heavily on the I-URTOs for their daily commutation. Hence, without increasing the city bus fare, most of these I-URTOs want to reduce the cost of their bus operations.

This can be addressed using a number of operations management decision problems such as efficiently/optimally identifying the number of buses with respect to every route, efficiently/optimally allocating buses to depots, increasing the number of routes where more revenue is generated, increasing the number of trips being taken in areas where the number of commuters is high and so forth. This study identifies and addresses one such decision problem related to the allocation of city buses to depots (ACBD) without changing the existing route and schedule of each bus.

The city buses in I-URTOs traverse various types of non-revenue generating distances. One such non-revenue generating distance is the 'Dead Kilometers' (Mathirajan et al. 2010). The dead kilometer is defined as the total distance traversed by buses from the depot to the respective starting point of the trip before the start of the first trip and from the ending point back to the depot after the end of the last trip. The report by the Central Institute of Road Transport (CIRT), which is committed to improve the efficiency and productivity of the transport sector with particular emphasis

on the state road transport undertakings of India (SRTU), indicated that more than 27 crores dead kilometers were incurred in 2016-2017 by all the city buses of I-URTOs. It is implicit that the annual losses incurred by the I-URTOs amount to several lakhs of rupees due to these 'dead kilometers.' In a metropolitan city like Bangalore in India, the Bangalore Metropolitan Transport Corporation (BMTC) operates a large fleet of approximately 6400 buses and 45 depots to maintain these buses. Due to such dynamic nature of city bus operations, the problem of dead kilometers has become complex.

Further, one cannot eliminate the dead kilometers. In such a case, the buses would have to be parked at the respective starting or ending point of the trip, but that would invite associated maintenance and security problems. Thus, an efficient ACBD needs to be done, which not only reduces the dead kilometers but also reduces the operating cost of buses. This is because both the dead kilometers and the operating cost vary depending on which depot the bus is allocated. This bears a direct positive influence on minimizing the city bus operations. So, this study considers the ACBD problem to reduce the cost of city bus operations by minimizing the dead kilometer cost (DKC) of I-URTO.

The paper is organized as follows: In Section 2, we discuss the problem description of the ACBD briefly. Section 3 presents a review of the existing literature on the problem and the countries where it has been applied. Section 4 discusses the methodologies proposed for the ACBD problem towards minimizing the cost of city bus operations. Section 5 briefly presents the required details for the performance analysis of the proposed methodologies. The analysis of the results with discussions is presented in Section 6. Finally, we conclude the paper in the last section.

2. Problem Description

Based on a quick analysis of literature, it is observed that the ACBD problem considers two different broad objectives: one is minimizing the dead kilometers, and the other is minimizing the dead kilometer cost. The problem of minimizing the dead kilometers has been widely addressed in India and other countries (Prakash et al. 1999; Mathirajan et al. 2010; Djiba et al. 2012; Eliiyi et al. 2012; Nasibov et al. 2013; Mahadikar et al. 2015) with some assumptions. However, since every bus has a different mileage for every unit of fuel, minimizing the dead kilometer cost (DKC) is a more appropriate objective function. This has been addressed in a few studies (Forbes et al. 1994; Kepaptsoglou et al. 2010; Kontou et al. 2014; Hsu et al. 2021) mainly in countries other than India. Hence, the main objective of this study is to optimize the cost of city bus operation by minimizing the dead kilometer cost (DKC) considering the fuel cost per kilometer. With this premise, the ACBD problem is described briefly as follows:

Let N be the number of buses available for optimal/efficient allocation to M number of depots. Each depot has a depot capacity (DC_j) for j=1,2...M depots. The values of the additional parameters: Dead Kilometers DK_{ij} if bus 'i' (i=1,2...N) buses) is allocated to depot 'j' (j=1,2...M) depots), Mileage/Kilometers per liter (kpl_i) of fuel for each bus 'i', and the price of fuel (P) are known. With these given data, the dead kilometer cost (DKC_{ij}) for each bus 'i' can be computed, w.r.t. to the each of the depot j as its choice for allocation, as follows:

$$DKC_{ij} = DK_{ij} \times \frac{P}{kpl_i}$$

Considering the derived data on dead kilometer cost DKC_{ij} applicable for every depot 'j' for each of the buses 'i', the objective of the ABCD problem is to allocate the given N number of buses to the available M number of depots by minimizing the total dead kilometer cost.

3. Literature Review

Sharma and Prakash (1986) addressed a prioritized bicriterion dead mileage problem. They initially formulated a model with the objectives of minimizing the cumulative distance traveled by the buses from the garage to starting point of the routes and minimizing the maximum distance among the dead mileage of the individual buses. Subsequently, as the second objective turned out to be not linear, they proposed a single objective transportation type approach to solving it. Raghavendra and Mathirajan (1987) addressed the optimal allocation of buses to depots problem for the Bangalore Transport Service (BTS) in India. They formulated their problem as a 0-1 Integer Linear Programming (0-1) ILP model with a single objective to minimize the overall dead mileage. Sridharan (1991) addressed the problem in a similar configuration as Raghavendra and Mathirajan (1987). The author modeled the problem as a transportation problem.

Mathirajan (1993) proposed an efficient heuristic procedure for the same data set of the BTS (Raghavendra and Mathirajan, 1987) with the objective of minimizing the dead mileage. Musso and Sciomachen (1997) addressed the

problem of optimal location and size of bus depots in the city of Genoa in Italy. The authors proposed to minimize the overall costs. They generated the empty path cost as a function of the fuel cost (gasoline) and the staffing cost. However, they formulated their model as a Mixed Integer Programming (MIP) model to minimize only the overall empty path for all the combinations of areas and depots. Perre and Oudheusden (1997) considered a hierarchical approach to address the combined problem of reducing the depot-route distance. They applied their model to a Bangkok Mass Transit Authority (BMTA) case in Thailand and claimed that their approach resulted in significant cost savings. Prakash et al. (1999) addressed the problem of optimizing the dead mileage through a nondominated solution approach.

Mathirajan et al. (2010) developed an experimental design based on data collected from the Bangalore Metropolitan Transport Corporation (BMTC) in the city of Bangalore in India to minimize the overall dead kilometers. They considered five heuristic algorithms and evaluated the performances of each of them against the optimal solution obtained from the (0-1) ILP model to determine the efficiency of these algorithms for large problems. Their results indicated that the heuristic algorithms took very meager computational time. However, they also addressed the immediate limitation of studying the problem as a transportation problem, thus not considering the best-known heuristics for (0-1) ILP. Nasibov et al. (2013) addressed the deadhead trip minimization problem to reduce the total fuel utilization due to dead mileage. They presented the results of four versions of the classical transportation model applied to the city bus services of Izmir. Mahadikar et al. (2015) addressed the same problem of optimally allocating buses to depots with the primary focus on minimizing dead kilometers.

Kepaptsoglou et al. (2010) proposed a Mixed Integer Quadratic Programming (MIQP) based mathematical model for the bus to depot allocation problem in the city of Athens in Greece to minimize the operating costs of deadhead kilometers and maximize the depot utilization. They considered a weighted sum approach due to the multi-objective nature of the problem. Kontou et al. (2014) introduced an extended version of the existing problem of the bus to depot allocation. They revised the earlier MIQP model given in Kepaptsoglou et al., 2010. In addition to the considerations of the existing model, the authors added the operating costs per depot to the objective function. They illustrated their solution through a small numerical example having 21 decision variables. Subsequently, to solve a large-scale MIQP model, the authors claimed their contribution, providing a hybrid Genetic Algorithm (GA) heuristic approach to solve it. The hybrid GA proved immensely superior in terms of the computational time and the objective function value.

Hsu et al. (2021) proposed an augmented (0-1) ILP model to address the problem of the depot, charging, and maintenance-related facilities' location for the comprehensive deployment of a mixed-bus system. The objective of their study was to minimize the total cost, which included the cost of the deadhead mileage, the cost of establishing depots, maintenance, and charging stations, cost of renting external buses minus the salvage value obtained after selling off the land of existing depots. As the problem turned out to be NP-hard, the authors proposed a decomposition-based two-stage heuristic algorithm to boost the computational efficiency. They illustrated the algorithm using case study data of a single bus operator in Taoyuan city, Taiwan.

The briefly reviewed literature on ACBD research is summarized in Table 1. From Table 1, it is observed that a scant treatment has been given in India for minimizing the cost of city-bus operations in general. There is particularly no research considering cost into the objective while efficiently/optimally allocating the buses to depots in India. This research gap is addressed in this study.

4. Proposed Methodologies for ACBD Problem

This problem can be viewed as a transportation problem (Vasudevan et al. 1993; Mathirajan et al. 2010). Most of the time, researchers and practitioners use efficient initial basic feasible solution (IBFS) methods to solve large-scale transportation problems and obtain near-optimal solutions. Considering this, more than 100 IBFS methods have been discussed in the literature (Mathirajan and Vimalarani 2021). The concept of the total opportunity cost matrix (TOCM) proposed by Kirca and Satir (1990) has been widely used while proposing IBFS methods. With this, the IBFS(s) are generally combined with two input matrices – (i) Transportation cost matrix (TCM) and (ii) total opportunity cost matrix (TOCM). Though many people are continuously introducing IBFS methods, almost every published research paper does not have a serious computational evaluation process to prove that the IBFS method(s) proposed by them consistently gives better results (Mathirajan and Vimalarani 2021). With this premise, Mathirajan et al. (2022) recently proposed many new variants of IBFS methods and considered various existing methods that are empirically proved to be better IBFS in the literature for performance analysis following an extensive computational evaluation process. Keeping this as a base research paper, the following 8 variants of IBFS methods: top 2 performing IBFS methods

according to the study by Mathirajan et al. (2022) and 6 good performing existing IBFS methods are considered to apply for the ACBD problem and to understand its relative performances:

RCWMCAM-DKCM: Row-Column Weighted Minimum-Cost-Allocation Method applied on Dead Kilometer Cost Matrix (DKCM)

RCWMCAM-DKOCM: Row-Column Weighted Minimum-Cost-Allocation Method coupled with Dead Kilometer Opportunity Cost Matrix (DKOCM)

VAM-DKCM: Vogel's Approximation Method applied on DKCM

VAM-DKOCM: Vogel's Approximation Method coupled with DKOCM

RAM-DKCM: Russell's Approximation Method applied on DKCM

RAM-DKOCM: Russell's Approximation Method coupled with DKOCM

MDM-DKCM: Maximum Demand Method applied on DKCM

MDM-DKOCM: Maximum Demand Method coupled with DKOCM

The step-by-step details of RCWMCAM and MDM are given in Annexure 1 as these are new IBFS methods proposed by Mathirajan et al. (2022) and Pargar et al. (2009) respectively. The other IBFS methods: VAM and RAM are popular and mentioned in many books (Winston 2004; Hillier and Lieberman 2010), so the step-by-step details are not given here. The above 8 variants of the heuristic algorithms are coded in Python. To verify their correct implementation, the Python implementation of each of these 8 heuristic algorithms is applied to a numerical problem and obtained the solution. Further, each of the 8 heuristic algorithms is manually applied on a numerical example and obtained the solution. The solution obtained manually using the heuristic algorithm: RCWMCAM is presented in Annexure 2. As these two sets of solutions are exactly matching for the numerical problem considered, the verification part of Python implementation is assured. Due to the brevity of the paper length issue, these details are not presented in the paper.

5. Performance Evaluation of the Proposed Methodologies for ACBD Problem

There are 3 components: problem instances, bench mark procedure(s), and performance measure(s) are involved in any performance analysis. The details of these components involved in this study are given as follows:

<u>Problem Instances</u>: In the absence of real-life data, the actual research practice is to propose a suitable experimental design for generating pseudo-random problem instances. Accordingly, in this study, the experimental design defined in Mathirajan et al. (2010) is modified/extended by introducing another problem factor: Mileage/Kilometers per Liter of the Fuel to represent the ACBD problem considered in this study. The summary of this modified experimental design is given in Table 2. A Python code is written for randomly generating problem instances using the experimental design given in Table 2. Accordingly, for each combination of the value of the parameters: number of depots, depot capacity, dead kilometers, kilometers per liter, 10 problem instances are randomly generated for performance evaluation of the proposed methodologies for the ACBD problem considered in this study.

<u>Performance Measure</u>: The performance analysis of the 8 heuristic algorithms considered in this study is carried out using the performance measure: average relative percentage deviation (ARPD), which is computed using the following equations:

$$ARPD_{i} = \sum_{i=1}^{N} RPD_{ii}/N$$
 (1)

$$RPD_{ij} = \left(D_{ij}/OTDKC_i\right) * 100 \tag{2}$$

$$D_{ij} = (TDKC_{ij} - OTDKC_i) \tag{3}$$

Where *i*: Problem instances $i \in [1, 30]$ instances

j: Proposed variants of IBFS methods and $j \in [1,8]$

Table 1. A summary on the existing literatures on the ACBD problem

| | | Problem | Objective Minim | | | Townsof | Source | | |
|----------------------------|------|---------|---------------------------|---------------------|-----------------|-----------------------------------------------|------------------------|----------------|--|
| Authors | Year | Туре | Dead Kilometer (DK) | DK Cost (DKC) | Methodology | Type of Model | of Data | Country | |
| Sharma and Prakash | 1986 | D | ✓ | | MM | LP | Numerical instance - 1 | | |
| Raghavendra and Mathirajan | 1987 | D | ✓ | | MM | (0-1) ILP | Case Data | India | |
| Sridharan | 1991 | D | ✓ | | MM | LP | Case Data | India | |
| Mathirajan | 1993 | D | ✓ | | HA | Heuristic | Case Data | India | |
| Forbes et al. | 1994 | D | | ✓ | MM | (0-1) ILP | ED | | |
| Musso and Sciomachen | 1997 | S | ✓ | | MM | MIP | Case Data | Italy | |
| Perre and Oudheusden | 1997 | S | √ | | MM and HA | MILP; and Greedy Heuristic | Case Data | Thailand | |
| Prakash et al. | 1999 | D | ✓ | | MM | INLP | Numerical instance - 1 | | |
| Kepaptsoglou et al. | 2010 | D | | ✓ | MM | MIQP | Case Data | Greece | |
| Mathirajan et al. | 2010 | D | √ | | HA and MM | Ranking Algorithm; VAM and (0-1) ILP | ED | India | |
| Djiba et al. | 2012 | D | ✓ | | MM | (0-1) MILP | Case Data | West Africa | |
| Eliiyi et al. | 2012 | D and S | ✓ | | MM | ILP | Case Data | Turkey | |
| Nasibov et al. | 2013 | D | ✓ | | MM | ILP | Case Data | Turkey | |
| Kontou et al. | 2014 | D | | ✓ | MM and M- HA | MIQP; and Hybrid GA | Case Data | Greece | |
| Mahadikar et al. | 2015 | D | ✓ | | MM | MILP | Case Data | India | |
| Hsu et al. | 2021 | D | | 1 | MM and HA | (0-1) ILP; and Greedy Heuristic | Case Data | Taiwan | |

Meaning of Abbreviations used: D – Deterministic, S – Stochastic, MM – Mathematical Model, HA – Heuristic Algorithm, M-HA – Meta HA, LP – Linear Programming, ILP – Integer LP, INLP – Integer Non-Linear Programming, MILP – Mixed Integer LP, MIP – Mixed Integer Programming, VAM – Vogel's Approximation Method, (0-1) ILP – Zero-One Integer LP, MIQP – Mixed Integer Quadratic Programming, GA – Genetic Algorithm, ED – Experimental Design

Table 2. A summary of an extended experimental design of Mathirajan et al. (2010)

| Problem Factor | No. of Levels | Values | | | | |
|------------------------------------------|---------------|--------------------------------------|--|--|--|--|
| Number of depots (ND) | 1 | 10 | | | | |
| Depot Capacity (DC) | 1 | [50-150] | | | | |
| Dead Kilometers (DK) | 3 | [5-200], [5-400], [5-600] | | | | |
| Mileage/Kilometers per Liter of the Fuel | 1 | [3.5 - 7] | | | | |
| Number of Problem Configurations | | $(1 \times 1 \times 3 \times 1) = 3$ | | | | |
| Number of Instances per Configuration | | 10 | | | | |
| Total Number of Problem Instances | | $(10 \times 3) = 30$ | | | | |

TDKC_{ij}: Total Dead Kilometer Cost yielded by the jth IBFS method for ith problem instance

OTDKCi: Optimal TDKC for 'ith' problem instance, yielded by the ILP Model

 D_{ij} : Difference between the 'Total Dead Kilometer Cost' obtained for the i^{th} instance from the jth variant of the IBFS method and the ILP for the i^{th} instance.

RPDij: Relative percentage deviation of 'jth' 'variant of the IBFS method for 'ith' problem instances

ARPD_i: Average relative percentage deviation of 'jth' variant of the IBFS method

N := 10 when ARPD is computed considering the number of problem instances w.r.t. each of the problem configuration

N := 30 when ARPD is computed considering entire problem instances

Bench Mark Procedure: For absolute performance evaluation of the 8 heuristic algorithms considered for the ACBD problem, the LP model proposed in Raghavendra and Mathirajan (1987) is considered as bench mark procedure.

6. Results and Discussions

Each of the 30 problem instances (representing the ACBD problems considered in this study) is solved using each of the 8 variants of the heuristic algorithms and the obtained 'total dead kilometer cost' yielded for ith problem instance by the jth IBFS method and the same is stored in TDKC(i,j). Each of the 30 problem instances is solved using the ILP model and the optimal 'total dead kilometer cost' obtained for each problem instance 'i' is stored in OTDKC(i). Using the results TDKC(i,j) and OTDKC(i), the relative percentage deviation of the solution obtained for each of the problem instances from each of the heuristic algorithms w.r.t. the optimal solution is computed using equation (2). This computed RPD(i,j) is presented in Table 3. Configuration-wise (that is, over 10 problem instances) and irrespective of the problem configuration (that is, over 30 problem instances), the average relative percentage deviation of the heuristic algorithm 'j' [ARPD(j)] is computed using equation (1), and the same is presented in Figure 1. The results presented in Table 3 and Figure 1 clearly indicates the following:

The recent study by Mathirajan et al. (2022) empirically and statistically proved that (a) the 2 variants of the proposed IBFS methods: RCWMCAM (out of 34 IBFS methods considered for performance analysis in their study) are outperforming, and (b) existing IBFS methods: MDM and RAM are relatively performing well in comparison with other existing IBFS methods in the literature. But these findings/observations are NOT matching with the results presented in Table 3 and Figure 1. From this one can infer that the best performing IBFS method(s) for the traditional transportation problem may not become best-performing ones when we apply these IBFS methods for the special case of transportation problem such as the ACBD problem!!

For the ACBD problem, on average, it appears that both variants of VAM (VAM applied with DKCM matrix and VAM coupled with DKOCM) are performing well. This is consistent with the earlier findings where VAM was proved to outperform the other heuristic, considering dead kilometers as an objective of the ACBD problem (Mathirajan et al. 2010).

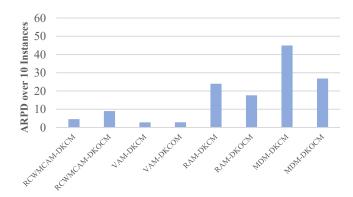
Out of 8 heuristic algorithms (IBFS methods) considered in this study for performance evaluation, the newly proposed IBFS method: **RCWMCAM** by Mathirajan et al. (2022), yielded next better results, followed by VAM.

The present study has limitations related to (a) computational experiments carried out - used randomly generated data instead of real-life data, (b) experimental design – used less number of problem configurations, (c) IBFS methods – considered only 2 proposed IBFS methods from the recent study by Mathirajan et al. (2022), and (d) the type of performance evaluation used. However, one practical implication of the present study is that the best-performing set of heuristics can now be computerized in a decision support system (DSS) environment, as the computational time required to solve real-life sized problem takes very meager computational time, which will eradicate the use of any expensive technology to solve the ACBD problem.

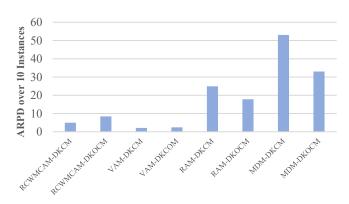
Table 3. RPD scores obtained by the proposed heuristic algorithms with respect to optimal solution

| No | | ACBD Proble | m - Paramete | rs | | RPD scores of | btained for the | e problem by t | he proposed l | heuristic algor | ithms | |
|-----------|----|-----------------|--------------|-----|------------------|-------------------|-----------------|----------------|---------------|-----------------|---------------|----------------|
| In st. | ND | DC | DK | NB | RCWMCAM -DKCM | RCWMCAM -DKOCM | VAM -DKCM | VAM- DKOCM | RAM -DKCM | RAM- DKOCM | MDM - DKCM | MDM - DKOCM |
| 1 | | | | 756 | 2.5 | 5.6 | 1.8 | 2.4 | 22.9 | 14.6 | 44.0 | 29.6 |
| 2 | | | | 708 | 3.5 | 8.7 | 2.6 | 2.5 | 29.8 | 18.2 | 44.2 | 28.0 |
| 3 | | | | 766 | 2.3 | 5.4 | 1.0 | 1.0 | 22.7 | 13.9 | 40.5 | 22.5 |
| 4 | | | | 660 | 5.0 | 8.9 | 2.4 | 3.6 | 23.4 | 16.2 | 47.6 | 27.6 |
| 5 | 10 | 550 1003 | 55 2003 | 840 | 2.7 | 4.7 | 0.6 | 0.9 | 24.4 | 19.6 | 44.8 | 29.3 |
| 6 | 10 | [50 - 100] | [5 - 200] | 739 | 5.2 | 12.0 | 3.3 | 2.3 | 22.2 | 19.0 | 43.9 | 23.3 |
| 7 | | | | 702 | 4.8 | 9.8 | 2.0 | 1.4 | 25.8 | 20.7 | 41.8 | 24.8 |
| 8 | | | | 656 | 10.3 | 17.2 | 6.6 | 6.9 | 20.1 | 18.2 | 48.2 | 25.2 |
| 9 | | | | 723 | 5.1 | 9.2 | 5.7 | 5.9 | 24.2 | 15.9 | 42.1 | 26.7 |
| 10 | | | | 721 | 4.3 | 8.7 | 2.4 | 1.8 | 24.3 | 20.0 | 52.2 | 31.2 |
| 11 | | | | 793 | 5.9 | 7.0 | 0.6 | 0.8 | 30.8 | 20.5 | 50.2 | 32.9 |
| 12 | | | | 742 | 6.3 | 10.3 | 1.4 | 1.4 | 22.0 | 17.5 | 49.3 | 25.6 |
| 13 | | | | 751 | 3.1 | 7.0 | 1.6 | 1.3 | 29.5 | 24.3 | 60.4 | 37.7 |
| 14 | | | | 806 | 5.8 | 9.2 | 1.0 | 2.5 | 19.4 | 13.5 | 50.2 | 27.5 |
| 15 | 10 | F50 1003 | F5 4003 | 667 | 5.0 | 10.2 | 2.4 | 2.3 | 19.4 | 17.2 | 52.9 | 28.4 |
| 16 | 10 | [50 - 100] | [5 - 400] | 737 | 4.2 | 6.3 | 2.8 | 2.6 | 22.0 | 18.6 | 59.3 | 41.6 |
| 17 | | | | 803 | 4.5 | 8.6 | 3.3 | 2.9 | 22.6 | 10.4 | 51.6 | 38.3 |
| 18 | | | | 738 | 3.8 | 8.3 | 2.1 | 3.1 | 24.6 | 14.4 | 55.6 | 37.1 |
| 19 | | | | 759 | 5.5 | 8.7 | 3.9 | 4.4 | 33.5 | 25.6 | 51.1 | 29.1 |
| 20 | | | | 822 | 5.3 | 8.7 | 2.0 | 2.8 | 25.2 | 16.2 | 50.0 | 32.3 |
| 21 | | | | 787 | 3.8 | 10.9 | 1.4 | 1.9 | 28.1 | 15.9 | 53.3 | 31.9 |
| 22 | | | | 741 | 4.3 | 9.5 | 3.0 | 3.0 | 25.6 | 16.6 | 50.5 | 28.1 |
| 23 | | | | 735 | 4.6 | 8.4 | 4.8 | 4.8 | 25.0 | 13.9 | 55.3 | 39.9 |
| 24 | | | | 747 | 4.4 | 7.7 | 1.2 | 1.3 | 32.9 | 19.4 | 47.8 | 27.9 |
| 25 | 10 | [50 100] | [5 600] | 741 | 6.0 | 14.3 | 3.0 | 3.7 | 21.2 | 15.5 | 49.9 | 29.1 |
| 26 | 10 | [50 - 100] [5 - | [5 - 600] | 773 | 7.1 | 8.6 | 2.8 | 3.2 | 21.6 | 20.5 | 51.8 | 33.2 |
| 27 | | | | 720 | 5.0 | 8.8 | 1.5 | 1.6 | 43.3 | 24.5 | 61.7 | 32.5 |
| 28 | | | | 752 | 7.8 | 13.1 | 1.2 | 1.4 | 35.1 | 22.0 | 51.8 | 33.9 |
| 29 | | | | 739 | 3.5 | 8.0 | 0.9 | 1.6 | 22.1 | 15.4 | 56.2 | 33.9 |
| 30 | | | | 729 | 5.4 | 9.7 | 3.6 | 4.0 | 27.5 | 19.0 | 47.4 | 28.3 |

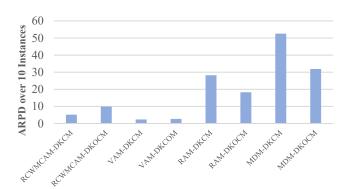
 $\underline{\textbf{Meaning of Abbreviations used}} : ND-Number of depots, DC-Depot Capacity, DK-Dead Kilometers, NB-Number of buses$



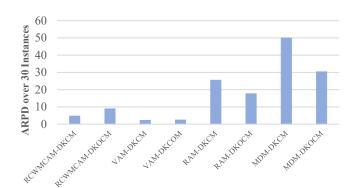
DK Range : [5 - 200], over 10 instances



DK Range: [5 - 400], over 10 instances



DK Range: [5 - 600], over 10 instances



Irrespective of DK Range, Over 30 instances

Figure 1. The average performance of the heuristics with respect to Optimal Solution

7. Conclusions

This study considers a new objective for the decision problem: ACBD of I-URTOs to minimize the cost of city bus operation. As this ACBD problem is a special type of transportation problem, the best-known IBFS methods reported in the literature are considered to apply to the ACBD problem to understand the status of these best-performing IBFS methods. For this research objective, a suitable performance analysis of the IBFS methods considered for the ACBD problem is carried out considering 30 randomly and systematically generated problem instances, which are generated from a suitable experimental design. The analysis of the results indicated that the best performing IBFS methods for transportation problem, as reported in the recent studies, are not necessarily performing as best when we applied these for the special case of the transportation problem such as ACBD problem. Further, the performance analysis indicated that the existing VAM outperforms for the ACBD problem. These inferences motivate us to address all the listed limitations of the present study as immediate future research activity. Further, each bus will yield a different pollution and accounts for different pollution cost. Hence, including the pollution cost in the objective function may affect the current best-performing algorithm and this becomes another future research issue. As this is a part of the Ph.D. dissertation work of the first author, many such future research activities are in the pipeline as immediate future research issues.

References

- Djiba, C. B., Balde, M., Ndiaye, B. M., Faye, R. M., and Seck, D., Optimizing dead mileage in urban bus routes: Dakar dem dikk case study, *Journal of Transportation Technologies*, vol. 2, no. 3, pp. 241–247, 2012.
- Eliiyi, U., Nasibov, E., Özkılçık, M., and Kuvvetli, Ü., Minimization of fuel consumption in city bus transportation: A case study for Izmir, *Procedia Social and Behavioral Sciences*, vol. 54, pp. 231–239, 2012.
- Forbes, M. A., Holt, J. N., and Watts, A. M., An exact algorithm for multiple depot bus scheduling, *European Journal of Operational Research*, vol. 72, no. 1, pp. 115–124, 1994.
- Hillier, F. S., and Lieberman, G. J., *Introduction to operations research*, 9th Edition, McGraw-Hill Higher Education, 2010.
- Hsu, Y.-T., Yan, S., and Huang, P., The depot and charging facility location problem for electrifying urban bus services, *Transportation Research Part D: Transport and Environment*, vol. 100, p. 103053, 2021.
- Kepaptsoglou, K., Karlaftis, M. G., and Bitsikas, T., Bus-to-depot allocation: Models and decision support system, *Journal of Transportation Engineering*, vol. 136, no. 7, pp. 600–605, 2010.
- Kirca, Ö., and Şatir, A., A heuristic for obtaining an initial solution for the transportation problem, *Journal of the Operational Research Society*, vol. 41, no. 9, pp. 865-871, 1990.
- Kontou, E., Kepaptsoglou, K., Charalampakis, A. E., and Karlaftis, M. G., The bus to depot allocation problem revisited: a genetic algorithm, *Public Transport*, vol. 6, no. 3, pp. 237–255, 2014.
- Mahadikar, J., Mulangi, R. H., and Sitharam, T. G., Optimization of bus allocation to depots by minimizing dead kilometers, *Journal of Advanced Transportation*, vol. 49, no. 8, pp. 901–912, 2015.
- Mathirajan, M., An efficient heuristic procedure for minimizing dead mileage in urban transport systems, *Journal of Transport Management*, vol. 17, no. 3, 1993.
- Mathirajan, M., Hariharakrishnan, C. V., and Ramachandran, V., An experimental evaluation of heuristic algorithms for bus-depot matching problem of urban road transport systems, *OPSEARCH*, vol. 47, no. 2, pp. 143–157, 2010.
- Mathirajan, M., and Meenakshi, B., Experimental analysis of some variants of Vogel's approximation method, *Asia-Pacific Journal of Operational Research*, vol. 21, no. 4, pp. 447-462, 2004.
- Mathirajan, M., and Rani, M. V., Observations on new initial basic feasible solution (IBFS) methods published in the literature for transportation problem, *Proceedings of the International Conference on Industrial Engineering and Operations Management*, pp. 201-210, Singapore, March 7 11, 2021
- Mathirajan, M., Reddy, S., and Rani, M. V., An experimental study of newly proposed initial basic feasible solution methods for a transportation problem. *OPSEARCH*, vol. 59, no. 1, pp. 102–145, 2022.
- Musso, E., and Sciomachen, A., Optimal location of bus depots in an urban area, WIT Transactions on the Built Environment, vol. 33, 1997.
- Nasibov, E., Eliiyi, U., Ertaç, M. Ö., and Kuvvetli, Ü., Deadhead trip minimization in city bus transportation: A real life application, *PROMET Traffic and Transportation*, vol. 25, no. 2, pp. 137–145, 2013.
- Pargar, F., Javadian, N. and Ganji, AP., A heuristic for obtaining an initial solution for the transportation problem with experimental analysis, *The 6th International Industrial Engineering Conference*, Sharif University of Technology, Tehran, 2009
- Prakash, S., Balaji, B. V., and Tuteja, D., Optimizing dead mileage in urban bus routes through a nondominated solution approach, *European Journal of Operational Research*, vol. 114, no. 3, pp. 465–473, 1999.
- Raghavendra, BG, and Mathirajan, M., Optimal allocation of buses to depots: A case study, *OPSEARCH*, vol. 24, no. 4, pp. 228-239, 1987.
- Reinfeld, NV and WR Vogel, Mathematical Programming, Englewood Cliffs, New Jersey: Prentice-Hall, 1958.
- Sharma, V., and Prakash, S., Optimizing dead mileage in urban bus routes, *Journal of Transportation Engineering*, vol. 112, no. 1, pp. 121–129, 1986.
- Sridharan, R., Allocation of buses to depots: A case study, *Vikalpa: The Journal for Decision Makers*, vol. 16, no. 2, 27–32, 1991.
- Storozhyshina, N., Pargar, F., and Vasko, F. J., A comprehensive empirical analysis of 16 heuristics for the transportation problem, *OR Insight*, vol. 24, no. 1, pp. 63–76, 2011.
- Van der Perre, P. P. G., and Van Oudheusden, D. D. L., Reducing depot-related costs of large bus operators a case study in Bangkok, *European Journal of Operational Research*, vol. 96, no. 1, pp. 45–53, 1997.
- Vasudevan, J., Malini, E., and Victor, D. J., Fuel savings in bus transit using depot-terminal bus allocation model, *Journal of Transport Management*, vol. 17, no. 7, 1993.
- Winston, W.L., Operations Research: Applications and Algorithms, Thomson, Belmont, 2004

Biographies

Rupkatha Ghosh is currently a Research Scholar at the Department of Management Studies in the Indian Institute of Science (IISc), Bengaluru, India, pursuing her research in Urban Road Transportation Organizations. She has a bachelor's degree (B.Tech.) in Civil Engineering from the National Institute of Technology (NIT), Durgapur, India. She has 1.5 years of experience as a senior civil engineer at Larsen and Toubro (LandT) Construction. Her areas of research interest include operations management, heuristic optimization, and urban road transport.

Dr. M. Mathirajan obtained his Ph.D. in Operations Management and MS degree by research in Applied Operations Research (OR) from IISc, Bangalore. He also received his MSc in Mathematics from Madurai Kamaraj University and Postgraduate Diploma in OR from College of Engineering, Guindy, Anna University. He has been working as faculty of IISc Bangalore since 1986 and has been a Chief Research Scientist since 2013. He is a Fellow of the Operational Research Society of India (FORSI). His areas of research interest include mathematical/heuristic optimization and research methods for operations and supply chain management, sequencing and scheduling, personnel scheduling, routing and scheduling of logistics, urban road transport, and container terminal logistics problems.

ANNEXURE 1:

A Step-by-Step detail of RCWMCAM-DKCM

- Step 1: If the given DKCM is not balanced, then balance the DKCM by introducing dummy demand (if total supply > total demand) or dummy supply (if total supply < total demand) with dead kilometer cost which is assumed as zero.
- Step 2: Record the minimum-cost for each row and column of the DKCM.
- Step 3: Compute minimum-cost-allocation for each row and column by multiplying the Minimum-Cost and possible feasible quantity to be allocated by considering each of the row and column based on the least dead kilometer cost in the respective row and column.
- Step 4: Compute the penalty-cost for each row and column by subtracting the first two lowest cell costs of the DKCM.
- Step 5: Compute weighted minimum-cost-allocation for each row and column by multiplying the penalty-cost and the minimum-cost-allocation.
- Step 6: Select the row or column with the highest weighted minimum-cost-allocation.
- Step 7: Allocate the feasible quantity with the least dead kilometer cost in the row or column with the highest weighted minimum-cost-allocation.
- Step 8: Repeat steps 2 to 7 until all demands have been met.
- Step 9: Compute the total dead kilometer cost for the feasible allocations of quantities using the DKCM.

A Step-by-Step detail of MDM-DKCM

- Step 1: If the given DKCM is not balanced, balance it by introducing dummy demand (if total supply > total demand) or dummy supply (if total supply < total demand) with dead kilometer cost which is assumed as zero. In case of unbalanced DKCM resulting in a dummy demand, it is important not to allocate any quantity to this dummy demand column until all 'real' demand is met.
- Step 2: Choose the column of DKCM with maximum demand. In case there is more than one column, go to Step 5.
- Step 3: Considering the identified column in Step 2 (or Step 5 or Step 6), allocate the maximum possible units to the cell based on the least dead kilometer cost in the column.
- Step 4: If the demand for the respective column is not met in Step 3, allocate units to the next least dead kilometer cell in the column, and continue until demand reduces to zero.
- Step 5: Compute the penalty cost for each column by subtracting the first two lowest cell costs of the DKCM and choose the one with the largest penalty cost. In case of ties in the largest penalty cost, go to step 6.
- Step 6: Select the column with the least dead kilometer cost.
- Step 7: Repeat steps 2 to 4 until all demands have been met.
- Step 8: Compute the total dead kilometer cost for the allocations of quantities using the DKCM.

ANNEXURE 2: A numerical example of the ACBD problem

The numerical example presented here has three depots and three buses.

Table 4 The Transportation tableau for the numerical example

| Bus | Dead Kilo | meters due to | ACBD | Mileage/Kilometers | Bus-Allocation (Supply Quantity) |
|----------------------------------|-----------|---------------|------|--------------------|-------------------------------------|
| | D1 | D2 | D3 | per liter | (Supply Qualitity) |
| B1 | 18.2 | 19 | 18.5 | 3.5 | 1 |
| B2 | 10.0 | 14.0 | 8.0 | 3.8 | 1 |
| B3 | 22.2 | 14.8 | 17.3 | 4.2 | 1 |
| Depot Capacity (Demand Quantity) | 1 | 1 | 1 | | |

Assuming the price of fuel as Rs. 102/-, and using the formula of DKC_{ij} in Section 2, the dead kilometer cost can be obtained as in Table 5.

Table 5 Total Dead Kilometer Cost (TDKC) tableau for the numerical example

| Bus | Dead Kilor | meter Cost | | Bus-Allocation (Supply Quantity) | | |
|----------------------------------|------------|------------|--------|----------------------------------|--|--|
| | D1 | D2 | D3 | (Supply Qualitity) | | |
| B1 | 530.4 | 553.71 | 539.14 | 1 | | |
| B2 | 268.42 | 375.78 | 214.73 | 1 | | |
| B3 | 539.14 | 359.4 | 420.14 | 1 | | |
| Depot Capacity (Demand Quantity) | 1 | 1 | 1 | | | |

A Walk Through of the IBFS Method: RCWMCAM on Dead Kilometer Cost (DKCM) Matrix

Working Mechanism – Iteration 1

| | D1 | D2 | D3 | Supply | Min Cost | Feasible Qty | Min Cost Allocation | Penalty Cost | Wt. Min Cost Allocation |
|----------|--------|--------|--------|--------|-------------|-----------------|------------------------|-----------------|----------------------------|
| B1 | 530.4 | 553.71 | 539.14 | 1 | 530.4 | 1 | 530.4 | 8.74 | 4635.70 |
| B2 | 268.42 | 375.78 | 214.73 | 1 | 214.73 | 1 | 214.73 | 53.69 | 11528.85 |
| B3 | 539.14 | 359.4 | 420.14 | 1 | 359.4 | 1 | 359.4 | 60.74 | 21829.96 |
| Demand | 1 | 1 | 1 | | 1 | | | | |
| Min Cost | 268.42 | 359.4 | 214.73 | | | | | | |

Allocation Qty w.r.t Iteration 1

| | D1 | D2 | D3 | Supply |
|--------|----|----|----|--------|
| B1 | | | | 1 |
| B2 | 1 | | | 0 |
| B3 | | | | 1 |
| Demand | 0 | 1 | 1 | 9 |

Few of King Mechanism – Iteration 3

| | D1 | D2 | D3 | Supply |
|----------|----|----|--------|--------|
| B1 | | | 539.14 | 1 |
| B2 | | | | |
| B3 | | | 420.14 | 1 |
| Demand | | | 1 | |
| Min Cost | • | | 420.14 | |

| Min Cost | Peasible Qty | Min Cost Allocation | Penalty Cost | Wt. Mm. Cos Allocation |
|-------------|-----------------|------------------------|-----------------|---------------------------|
| 539.14 | 1 | 539.14 | 539.14 | 290671.93 |
| 420.14 | 1 | 420.14 | 420.14 | 176517.61 |

| | D1 | D2 | D3 | Supply |
|--------|----|----|----|--------|
| B1 | | | 1 | 0 |
| B2 | 1 | | | 0 |
| B3 | | 1 | | 0 |
| Demand | 0 | 0 | 0 | |

Allocation Qty w.r.t Iteration 3

| Min Cost | 420.14 |
|---------------|--------|
| Feasible Qty | 1 |
| Min Cost | |
| Allocation | 420.14 |
| Penalty Cost | 119 |
| Wt. Min. Cost | |

Allocation Qty w.r.t Iteration 2

| Allocation | | | | 49996. | 66 | | | | | | | | | | | | |
|-----------------------|------|-----|-----------|----------------------|--------|--------|----------|----------|---------|-------------------|-------|----------------------------|-----|-----|-----|----------|--------|
| | | D1 | D2 | D3 | Supply | Min | Feasible | Min Cost | Penalty | Wt. Min Cost | t | | | D1 | D2 | D3 | Supply |
| 200240 | | | | | Opti | | Solution | obtained | | thellogram | erica | B1 | | | | | 1 |
| B1 | | | 553.71 | 539.14 | ſ | 539.14 | 1 | 539.14 | 14.57 | 7855.27 | | B2 | 2 | 1 | | | 0 |
| B2 | | | NIA TRACT | | | | | | | • • | | _B3 | | _ | 1 | | 0 |
| (a) | Pytl | hon | 359.4 | 420.1 4 - | 1 | 359.4 | 1 | 359.4 | 60.74 | 21829. 90) | Mai | iual ^{B3} Dema | and | Pro | ees | 1 | |
| Demand | | | 1 | 1 | | | | | | | | Denne | and | 0 | U | o (14) o | |
| Min Cos | | 0 | 1 | 2 | | | | | | | | D1 | D2 | D | 3 | Supp | ly |
| Feasible Q Min Cos | 0 | 0.0 | 0.0 | 1.0 | | | | | | В | 1 | - 3 | | 1 | S . | 0 | |
| Allocatio | | | | | | | | | | B | 2 | 1 | | | | 0 | 2 |
| Penalty Cos | 1 | 1.0 | 0.0 | 0.0 | | | | | | B2 | 3 | | 1 | | | 0 | |
| Wt. Min Co | | | | | | | | | | Dem | and | 0 | 0 | (|) | | |

Total Dead Kilometer Cost = 1166.96

2 0.0 1.0 0.0

Allocation

Demand