Available online at www.sciencedirect.com
SciVerse ScienceDirect
Procedia - Social and Behavioral Sciences 54 (2012) 231 – 239
Procedia
Social and Behavioral Sciences

EWGT 2012

15th Meeting of the EURO Working Group on Transportation

Minimization of fuel consumption in city bus transportation: A case study for Izmir

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Abstract

In this study, we handle a real life optimization problem of a metropolitan city bus service. The problem's focus is the fuel consumption due to dead mileage, given the bus requirements of all route schedules. We obtain the optimal route bus-garage allocations that minimize the total distance covered in all pull-out and pull-in trips, and reach significant improvement levels with respect to the current situation. We consider the midday demand fluctuations on each route, so that some of the buses have to make extra pull-in and pull-out trips before parking at their night garages after ending their last service trips. Moreover, we develop a multicriteria model which takes into account the fuzzy levels of passenger satisfaction and parking safety combined with the previous minimization objective.

Keywords: Multiple-depot bus scheduling; Dead mileage; Fuel consumption; Fuzzy parametric approach; Transportation planning.

1. Introduction

The optimal planning of public transportation services is one of the most important goals of the urban administrations for its both economical and environmental effects. Along with the size of the city, even the impact of a slight relative reduction in the costs of some key activities might lead to considerable budget savings. One of such important cost factors is obviously the fuel consumption of the vehicles, comprising the major part of the energy requirements of the whole transportation system. In addition to the amount of fuel used for the

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 doi:10.1016/j.sbspro.2012.09.742

active scheduled trips, a significant portion is due to the idle distances covered by the vehicles between the garages or depots and route termini without carrying any passengers.

In this study, we try to minimize the total distance covered in all pull-out and pull-in trips. A pull-out trip occurs when a bus leaves a garage to reach its start location of a scheduled trip, which corresponds to the beginning or ending terminal of a route [1]. Similarly, a pull-in trip is in the opposite direction, namely when a bus returns to the garage from the end location of its trip. In the case of Izmir city bus service, the deadhead trips which are defined as the idle distances that are covered between the same route's or different routes' termini, are not considered since they are rarely employed. So henceforth in this paper, we will use the term "dead mileage" to denote the sum of all pull-out and pull-in trip distances.

Izmir, the third largest city of Turkey, covers a metropolitan area of over 5,500 km^2 and a population of about 4 million inhabitants [2]. The city bus service is managed by ESHOT General Directorate and is operated by two corporations, including ESHOT itself, on 323 routes, and 10 garages. In a previous study, Nasibov et al. [3] implement four versions of the classical transportation model for assigning buses to each garage for minimizing the fuel consumption due to dead mileage. Their versions differ from each other depending on scenarios whether the garages and routes are operated by one firm (centralized models) and whether the capacities of the garages can be expanded (uncapacitated models). Since the amount of dead mileage is much less in weekends, they only focus on the weekday bus schedules to obtain the optimal bus-garage allocations for each route. Their solutions promise 8 to 22% improvements in the more implementable capacitated models. They do not consider the hourly demand fluctuations in bus requirements of routes and so it is assumed that, all buses serve without any pull-in trips in the middle of the day except the last return to their night parking garages. In this study, we extend their approach firstly in this changing demand levels aspect. Specifically, using the same minimization objective, each weekday is divided into six periods to reflect the different demand levels in midday concerning the number of buses running on each route.

Prakash et al. [4] consider the bus-garage allocation problem with two objectives, solutions of which are nondominated plans to allocate buses to the terminal points of their routes and to the parking garages at nights. In addition to the dead mileage objective, they aim to minimize the maximum distance among the distances covered by individual buses from depots to route termini. Willoughby [5] analyses the locations of the garages of Vancouver Local Transit System in Canada and the allocation of the buses to these garages with a mixed integer programming model. They consider the capital investment costs for construction of new garages besides dead mileage costs. By solving this model, they attain a 5% reduction in total costs and a 12% reduction in total pull-out and pull-in trip expenses. Dahiya and Verma [6] consider a class of the capacitated transportation problems by establishing their equivalence with a balanced capacitated transportation problem for dead mileage minimization. Kepaptsoglou et al. [7] propose a decision support system model that minimizes deadhead costs by maintaining the garages at ideal operating levels. The model is implemented for the bus operator in Athens, Greece, and the occupancy balance of the garages were conserved along with a 10% reduction in the expenses related to dead mileage.

In the next section, we define our problem in detail and present the related models with accompanying solution results obtained by using actual data in Section 3. Apart from the operational aspect depending on the current bus requirements and garage capacities, we also evaluated the obvious tactical scenario involving the possible interchange of some routes between the two operating firms by converting the original model to the centralized version. The environmental aspects regarding the carbon emission levels of the new solutions are also summarized in that section. In Section 4, we present a more general model which also considers passenger satisfaction and parking safety objectives using fuzzy parameters for number of allocated buses and garage capacities due to different levels of route-bus requirements defining congestion issues both within a bus or a garage. We conclude with future study topics in the last section.

2. Problem Definition

Our problem is the assignment of available garages to the pulling-out or pulling-in buses in each demand period of the service day in a manner that daily dead mileage is minimized. Hence, there is a straightforward dynamic allocation process using bi-directional inventory flow constraints. We assume that all route schedules are determined in advance providing us the required and unnecessary number of buses at each route terminal for each period.

Only one type of bus is considered in our problem, but the operating firm distinction at each route may implicitly involve such differentiation. As in our study, bus requirements demanded from different operators for the same route might be thought as different types of buses, according to their seated passenger capacities, sizes and accessibility features.

The time intervals corresponding to different demand periods used in our problem are listed in Table 1. The sixth period and the first are connected and within these periods there are only one-directional bus movements, respectively just pull-ins and pull-outs.

Table 1. Time intervals of different periods of route-bus demands in a weekday

Period no	Period interval
1	06:00-09:00
2	09:00-13:00
3	13:00-16:00
4	16:00-20:00
5	20:00-24:00
6	24:00 and later

Another assumption is that, if a bus begins its scheduled trip on any terminal (starting or ending stop) of a route, its next return (pull-in) to a garage will be from the same terminal location. Arising from the periodic nature of the problem and differences in route demand fluctuations throughout a day, night parking garages and midday parking garages of a bus may differ. Indeed, the problem formulation seeks for that kind of differences to take advantage from the sparseness and availability of more central garages during periods of demand peak like rush hours. All movements occur at the beginning of period intervals.

Each bus is dedicated only to one route apart from the operator it belongs to, so that a pulled-in bus parked at a garage in midday cannot be assigned to a different route within the following periods.

Nomenclature

P	set of different demand periods in a weekday, $\{1,...,z\}$, where z= number of periods
p	period index
I	set of bus routes, $\{1,...,h\}$ where h= number of routes
i	route index
J	set of parking garages, $\{1,...,g\}$ where g= number of garages
j	garage index
K	set of starting points (termini) for each route, $\{1,...,s\}$, where s= number of terminals
k	terminal index

F	set of operator firms, $\{1,...,o\}$, where o= number of operators
f	operator index
d_{ijk}	distance of garage j to the terminal k of route i (km)
C_{jf}	capacity of garage j for the operator f (number of buses)
C_j	capacity of garage j (number of buses)
δ_{pikf}	number of buses owned by operator f that should begin their scheduled trips to terminal k of route i in period p
δ_{pik}	number of buses that should begin their scheduled trips to terminal k of route i in period p
λ_{pikf}	number of buses owned by operator f that should be pulled into (parked at) a garage returning from terminal k of route i in period p
λ_{pik}	number of buses that should be pulled into a garage from terminal k of route i in period p

Using the nomenclature given above, our problem data can be summarized as follows: There are h = 323 routes, g = 10 garages with a total capacity of around 1,600 buses operated by o = 2 firms (ESHOT and IZULAS). Each route has the trivial s = 2 termini, while k = 1 means the starting and k = 2 the ending bus stops. As previously mentioned, the flow parameters δ_{pikf} and λ_{pikf} are defined over z = 6 periods.

The available garage capacities used in our problem are listed in Table 2. Despite the first model supports otherwise, a garage is exclusively owned by one of the firms in the real case. First eight of the garages are operated by ESHOT and the remaining two by IZULAS.

Table 2. Garage capacities

Garage no	Garage name	Capacity for ESHOT buses	Capacity for IZULAS buses
1	Gediz	234	0
2	Inciralti	225	0
3	Adatepe	270	0
4	Mersinli	216	0
5	Sogukkuyu	63	0
6	Cigli	225	0
7	Urla	31	0
8	Torbali	23	0
9	Stad	0	153
10	Belkahve	0	198

As a comparison base for the developed models, current daily dead mileage levels for weekdays are obtained by averaging the actual smart card data collected from all bus trips of each operating firm in November 2011. These values are 15,247 and 4,237 km respectively for ESHOT and IZULAS, 19,484 km in total. Regarding the fuel consumption figures, we used a 50 L/100 km average rate for each bus. As for the cost evaluations, diesel price per liter was taken as € 1.3. Using these values, annual fuel consumption cost due to dead mileage amounts to € 4,255,000.

3. Dead Mileage Minimization Models

Our first model is the most representative one regarding the current situation. There is the operator distinction and garage capacities cannot be expanded. Concerning its applicability in a shorter planning horizon, we call it as the operational bus-garage allocation model. The second one is the centralized version of the first, and is named as the tactical bus-garage allocation model.

3.1. Operational Bus-Garage Allocation Model

There are two types of decision variables used in both models. First one defines the movements between garages and route termini, and the other corresponds to the number of buses parked at each garage at each period. As it is formulated in the model constraints below, both types of variables are directly related to each other.

Particularly for the first model, the decision variables are denoted as follows:

- x_{pijkf} : the number of buses owned by operator *f*, which should move from garage *j* to the terminal *k* of route *i* at period *p*,
- y_{pijkf} : the number of buses owned by operator *f*, which should move from the terminal *k* of route *i* to garage *j* at period *p*,
- a_{pijf} : the number of buses owned by operator *f* running on route *i* and parked at garage *j* at period *p*.

All the decision variables and problem parameters being nonnegative integers, the integer programming allocation model takes the following form.

$$\text{Minimize } \sum_{p\in P}\sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{f\in F} d_{ijk}(x_{pijkf}+y_{pijkf}) \tag{1}$$

subject to:

$$\sum_{j\in J} x_{pijkf} = \delta_{pikf} \qquad \forall p\in P, \forall i\in I, \forall k\in K, \forall f\in F \tag{2}$$

$$\sum_{j\in J} y_{pijkf} = \lambda_{pikf} \qquad \forall p\in P, \forall i\in I, \forall k\in K, \forall f\in F \tag{3}$$

$$a_{1ijf} = a_{6ijf} - \sum_{k\in K}(x_{1ijkf} - y_{1ijkf}) \qquad \forall i\in I, \forall j\in J, \forall f\in F \tag{4}$$

$$a_{pijf} = a_{(p-1)ijf} - \sum_{k\in K}(x_{pijkf} - y_{pijkf}) \qquad \forall p\in P-\{1\}, \forall i\in I, \forall j\in J, \forall f\in F \tag{5}$$

$$\sum_{i\in I} a_{pijf} \le C_{jf} \qquad \forall p\in P, \forall j\in J, \forall f\in F \tag{6}$$

The objective (*1*) minimizes the distance covered by all pull-out and pull-in movements over all periods. The constraints (*2*) and (*3*) define the demand fluctuation levels of each route terminal and the corresponding bus movements from and to all garages. The number of buses parked at night is related to the first trips of the morning in (*4*), where y_{1ijkf} are obviously all zero. The garage capacities actually used for consecutive periods are described simply by differences in directional flows (*5*), all of which should satisfy (*6*), the available capacities of all garages for each operator firm.

The model was solved by using IBM ILOG CPLEX 12.1 optimization library in forty seconds on a Windows 7 PC configuration with 4 GB RAM and 1.8 GHz triple core processor. All input data and output results are stored in MS Excel files.

Reaching a minimum level of daily dead mileage at 17,910 km, a complete implementation of the optimal bus-garage allocations provided by the solution of this realistic model promises an 8.1% reduction in fuel consumption and an annual saving around € 350,000.

The number of buses parked at all garages at nights is 1,404, followed by 487 and 464 in periods 2 and 3 respectively. There is a total of 3,416 pull-in and pull-out trips daily, 77% of which occurs in rush hours (periods 1 and 6) and correspond to 79% of all the dead mileage. Some important figures for each period are summarized in Table 3. All values in the table are aggregated over garage allocations using the solution values of the decision variables.

Table 3. Summary results of the operational bus-garage allocation model

Operator	ESHOT						IZULAS					
Periods	1	2	3	4	5	6	1	2	3	4	5	6
Dead mileage (km)	5,672	1,924	186	1,167	0	4,733	1,852	270	7	212	0	1,885
Buses parked	29	423	402	139	139	1,129	3	64	62	16	16	275
Bus movements	1,100	400	21	263	0	990	272	61	2	48	0	259

3.2. Tactical Bus-Garage Allocation Model

As stated in the beginning of Section 3 there is no operator distinction in this model's structure; every garage and bus belongs to the same one firm. The objective function (*1*) and all the constraints (*2*) to (*6*) are identical with the first model, but only the operator firm indices and the corresponding summations. They are removed from each occurrence in the model, either a decision variable or a parameter with their new versions being respectively x_{pijk}, y_{pijk}, a_{pij}, δ_{pik}, λ_{pik} and C_j.

The optimal bus-garage allocations of the tactical model can be used to change some routes between the current operating firms by simply considering the allocated garages, all of which are exclusively operated by one of the operators in the actual situation. So according to Table 2, any route bus assigned to Stad garage (no. 9) should therefore be assigned to the operator IZULAS naturally for the sake of reaching the same objective function value in the operational model. Thus, the demand parameters δ_{pikf} and λ_{pikf} of the operational model will be updated using the results of the tactical model.

The solution of the tactical model improves the current status by 21.9% and reduces the fuel costs about € 930,000 annually. Although employing the changes to reach this solution might take longer as compared to the one demanded by the operational allocation model due to legal or organizational issues incurred, the gainings summarized above justify the effort. The daily requirement of all routes is found to be satisfied by 1,409 buses, which cause 15,218 km dead mileage.

The environmental perspective of the problem is at least as important as the cost reduction issue, especially for cities like Izmir. Along with the size of the city, even the impact of a slight improvement in fossil fuel spending rates might contribute much. For this reason, we also summarize some straightforward environmental gains arising from the new carbon emission levels, which can be attained if the new solutions are implemented. If the operational model allocations are employed with some further enhancements, it is found that the annual CO_2 emission due to dead mileage will be reduced by 330 tons, equivalent to the biological labor of 991 trees.

Similarly, 618 tons of less CO_2 will be produced when the optimal solutions of the tactical model are implemented matching 1853 trees' annual work [8].

In the next section we present a more generalized multicriteria decision making model, which also considers customer satisfaction and parking safety objectives.

4. A Fuzzy Multicriteria Approach

In this section, we extend the operational allocation model with two more criteria involving fuzziness. First is about passenger satisfaction, associated with the number of buses used on a route. The second is concerned with parking safety in garages, simply related to the number of buses parked that might cause traffic congestion affecting bus maneuvers within the garage parking spaces. As the other models presented in the previous section, no vehicle type distinction is considered either in this new model.

El-Wahed [9] proposes a fuzzy programming approach to solve a multi-objective transportation problem. The performance of each solution is measured due to the degrees of closeness to the ideal solution using a family of distance functions. He also shows that the fuzzy approach outperforms the interactive procedure as the number of objectives and constraints increases. Yeh et al. [10] evaluate the overall performances of 10 bus operator companies by using fuzzy multicriteria analysis. In another study, a decentralized two-level linear programming approach is implemented for a real-world transportation problem for two different decision making perspectives by applying an interactive fuzzy programming method [11]. They obtain a satisfactory solution to the problem by considering both the transportation cost minimization and profit maximization objectives with respect to two parties involved.

We assume that as the number of buses serving on a route that satisfies the same amount of passenger demand increases, the average passenger load of a route trip and the waiting times on route bus stops will decrease. Both of these criteria have positive influence on the passengers' opinions about the performance of the provided transport service.

Let $\tilde{w}_i$ be the average number of passengers carried per trip on route i. Dividing the passenger demand b_i of the route by this parameter gives us $\tilde{r}_i$, the fuzzy parameter for number of trips required on that route. If the route demand is defined on the time interval $[t_1, t_2]$, then the average lag between each trip of the route becomes $\tilde{q}_i = (t_2 - t_1) / \tilde{r}_i$. Finally, this parameter is used to find the bus requirements of the route with the total round trip duration l_i (including active trip durations in both direction and driver's idle time between trips) as follows: $\tilde{m}_{i,1} = l_i / \tilde{q}_i$. If the operator firm has a different policy for the lag time between route trips, say $\tilde{q}_{i,req}$, then the number of buses required will be evaluated simply as $\tilde{m}_{i,2} = l_i / \tilde{q}_{i,req}$. Therefore we can take the parameter $\tilde{m}_i = \max(\tilde{m}_{i,1}, \tilde{m}_{i,2})$ for utilizing in the model. Adapting this approach to the model presented in Section 3.1, we will have the fuzzy numbers $\tilde{\delta}_{pikf}$ and $\tilde{\lambda}_{pikf}$ having the degree $\beta \in (0,1]$ of passenger satisfaction as shown in Fig 1. It should be noted that, $\tilde{\lambda}_{pikf}$ has also a similar decreasing linear membership function as the fuzzy interval shown on Fig 1(b), but with degree β.

For parking safety, the definition of the garage capacity parameter $\tilde{C}_{jf}$ is a decreasing linear membership interval as shown in Fig.1(b), in parallel to the one defined for the number of pull-in trips at each period. The safety level μ for each garage is simply the ratio $(C_{jf,\max} - C_{jf}) / (C_{jf,\max} - C_{jf,\min})$, where $C_{jf,\min}$ is the maximum number of buses of operator f that can be located at garage j without forming any risks concerning parking safety and congestion and $C_{jf,\max}$ is the actual maximum capacity.

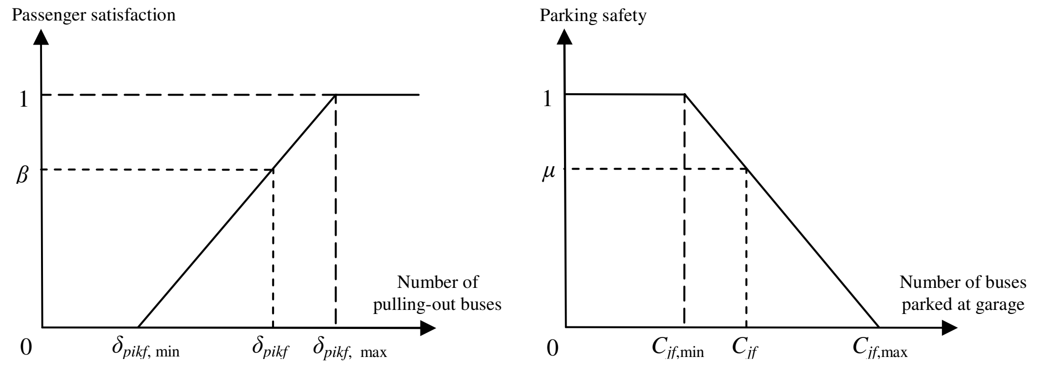

Fig. 1. Fuzzy parameters for the (a) required number of $\tilde{\delta}_{pikf}$, pull-out trips; (b) $\tilde{C}_{jf}$, garage capacities for parking safety

Clearly, the parking safety and passenger satisfaction criteria defined as above collide with each other since one favors a large number of buses, the other less. More specifically, in terms of allocation periods the most important one that affects our problem solution is the last period, namely the night parking garage utilizations. Yet in any case having both criteria combined in the same objective level of fuzziness, we would attain the minimum of maximum degrees for β and μ. Summing up all the discussion above, the multicriteria integer programming approach for operational bus-garage allocation is presented as follows.

$$\text{Minimize} \sum_{p\in P}\sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\sum_{f\in F} d_{ijk}(x_{pijkf} + y_{pijkf}) \qquad (1)$$

$$\text{Maximize } \alpha \qquad (7)$$

subject to:

$$\sum_{j\in J} x_{pijkf} \geq \delta_{pikf,\min} + \alpha(\delta_{pikf,\max} - \delta_{pikf,\min}) \qquad \forall p\in P, \forall i\in I, \forall k\in K, \forall f\in F \qquad (8)$$

$$\sum_{j\in J} y_{pijkf} \geq \lambda_{pikf,\max} + \alpha(\lambda_{pikf,\min} - \lambda_{pikf,\max}) \qquad \forall p\in P, \forall i\in I, \forall k\in K, \forall f\in F \qquad (9)$$

$$a_{1ijf} = a_{6ijf} - \sum_{k\in K}(x_{1ijkf} - y_{1ijkf}) \qquad \forall i\in I, \forall j\in J, \forall f\in F \qquad (4)$$

$$a_{pijf} = a_{(p-1)ijf} - \sum_{k\in K}(x_{pijkf} - y_{pijkf}) \qquad \forall p\in P-\{1\}, \forall i\in I, \forall j\in J, \forall f\in F \qquad (5)$$

$$\sum_{i\in I} a_{pijf} \leq C_{jf,\max} + \alpha(C_{jf,\min} - C_{jf,\max}) \qquad \forall p\in P, \forall j\in J, \forall f\in F \qquad (10)$$

$$\sum_{i\in I}\sum_{j\in J} a_{6ijf} \leq B_f \qquad \forall f\in F \qquad (11)$$

The objective function (*1*) and the constraints (*4*) and (*5*) are also included in this bicriteria optimization problem as in the operational allocation model (Section 3.1). Constraints (*8*), (*9*) and (*10*), are the modified versions of (*2*), (*3*) and (*6*) respectively. As the satisfaction level α of the objective (*7*) increases, the optimal value of (1) will increase (at least will not decrease) as well. The last constraint (*11*) is added so that for some degrees of α, the number of all route buses parked at their night garages will not exceed the total number of available buses actually owned by each firm. All decision variables and parameters of this model are also defined as nonnegative integers, except $\alpha \in (0,1]$.

For simplifying the solution of the problem, the objective (*7*) can be dropped and taken as a parameter. In this manner, the multicriteria problem will be converted into an integer minimization problem in the same form modeled as above, where all decision variables depend on the value of the parameter α.

5. Conclusion and Future Study

In this study, two bus allocation models are developed for solving the dead mileage minimization problem of a metropolitan city transport system. Real-life implementations of both models are possible within short planning horizons, and the potential positive outcomes are stated by presenting some numerical results.

Besides the usual cost concerns, focusing also on the environmental and social aspects of the public transportation will surely contribute to improve the living standards in metropolitan areas. For this purpose, some straightforward environmental gains arising from the carbon emission levels of the new solutions are presented. These results provide an optimistic perspective about the impact of larger-scaled optimization projects planned for the future of the city.

Moreover, a new bicriteria model that incorporates a fuzzy objective combining passenger satisfaction and parking safety degrees is proposed. Therefore, we also aim to reach a certain level of service quality besides the usual cost reduction and environmental improvements in urban life with respect to fuel consumption.

Regarding the fuzzy parametric approach, our next study will comprise finding the Pareto-efficient frontier for the bus-garage allocation problem using several degrees of α against the optimal dead mileage values. Then, by including the bus type distinctions and driver workload balancing, we intend to extend the problem boundary to include more detailed fleet planning and crew scheduling. Our future research will also cover the optimal bus scheduling with transit network design considerations that incorporate other modes of transport in Izmir, namely metro, ferry and light rail systems.

Acknowledgements

This study is supported by Izmir Metropolitan Municipality ESHOT General Directorate, Department of Transport Planning and Statistics.

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