

Research Article

Optimization of Headways and Departure Times in Urban Bus Networks: A Case Study of Çorlu, Turkey

Huseyin Ceylan ¹ and Tayfun Ozcan ²

¹Civil Engineering Department, Faculty of Engineering, Pamukkale University, Denizli 20160, Turkey

²Department of Construction Technologies, Yatağan Vocational School, Muğla Sıtkı Koçman University, Muğla 48500, Turkey

Correspondence should be addressed to Huseyin Ceylan; hceylan@pau.edu.tr

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The traffic congestion, which has become one of the major problems of developed and developing countries, has led to a shift in the way public transport systems are viewed, and it has accelerated efforts to increase the efficiency of these systems. In recent studies, several approaches, in which both user and operator benefits are evaluated together in order to increase the demand for public transportation systems and to ensure the sustainability of these systems, are emphasized. In this study, a bilevel simulation/optimization model is developed to optimize service headways and departure times of first buses from the beginning of the routes in urban bus networks. At the upper level of the proposed model, a multiobjective function representing user and operator costs is evaluated using the metaheuristic harmony search (HS) optimization technique. The transit assignment problem, which represents the distribution of transit users over the routes, is handled at the lower level. In the proposed model, the transit assignment problem is solved by the timetable-based assignment approach with VISUM transport planning software. The timetable-based transit assignment is an approach in which the perception errors within the users' route choice are taken into consideration and the transfer wait times can be precisely calculated. The proposed model is applied to a real-life urban bus network of the Çorlu district (Tekirdağ, Turkey), and the effectiveness of the model on a medium-sized urban bus system has been demonstrated. The results show that the user and operator benefits can be simultaneously increased by adding an initial departure offset parameter to the problem.

1. Introduction

Traffic congestion due to increasing demand for private car use brings health and environmental problems, as well as imposes a heavy burden on the economies of developing and developed countries. Along with the increase in fuel consumption of motor vehicles in the heavy traffic, the harmful gases threaten human health by polluting the environment and trigger global warming by increasing the effect of greenhouse gases [1]. Behrens and Egenhofer [2] state that the transportation sector is responsible for a quarter of all greenhouse gas emissions in European countries. Therefore, it is important to organize public transportation systems which can be alternative to private cars in terms of safety, reliability, comfort, and economy criteria in order to avoid environmental and health problems and to minimize the amount of energy required in the transport sector. Central

and local governments trying to reduce traffic congestion by making public transportation services more attractive are investing in public transport systems in the direction of short- and long-term strategies as well as even taking measures to limit individual car sales [3]. However, public transportation systems, which are the most important solution to the traffic congestion, cannot meet the increasing travel demand due to poor planning, design, and management. In studies evaluating the performance of public transportation systems, it is revealed that the primary problem related to the transit services in developing countries is the lack of capacity during peak hours [4–6]. This problem can be solved by increasing the fleet size and service frequency during peak hours, which leads to an increase in operating costs that reduces the operator profit margins. However, in order to ensure the sustainability of transit services, not only the users' expectations but also the

operator's expectations must be met. In public transportation, operators aim to achieve a certain profitability by considering their limited budgets and available bus fleets, while users generally expect a combination of high service quality and minimum travel time. At this point, service quality can be considered as a function of comfort level and reliability, while travel time consists of in-vehicle time, waiting time, and transfer time. Therefore, the trade-off between user and operator objectives should carefully be considered in public transport planning. Considering that the conventional public transportation planning process includes route design, timetable preparation based on the available fleet of buses, and crew scheduling steps, accurately determined that frequencies of bus lines play an important role in this process. Oudheusden and Zhu [7] state that poorly prepared timetables lead to an overloading of buses. On the contrary, accurate timetables, which are determined based on optimized frequencies, may reduce operating costs and increase user benefits. In the relevant literature, several studies concerning the optimization of service frequencies in public transportation networks have focused on the transit network design problem (TNDP) [8–20]. In the TNDP, which is generally formulated as the minimization of the sum of user and operator costs, the optimal transit routes and associated frequencies are sought. On the contrary, there are few studies that deal with the service frequencies for fixed bus route configurations [7, 21, 22].

Baaj and Mahmassani [11] developed a Transit Routes Analyst (TRUST) program in order to solve the TNDP. In their study, the TNDP was formulated as the minimization of an overall cost measure including operator costs and user costs. The former was considered as total trip time of all services during the analysis period. On the contrary, user costs were taken into consideration as the total travel time for all transit users, which requires the assignment of the origin-destination (O-D) matrix to the transit routes. At this point, a lexicographic strategy, which was previously presented by Han and Wilson [23], was adopted in TRUST. In this strategy, it was assumed that the users avoid transfers when choosing their routes among competing ones between their origins and destinations. From this point of view, the number of transfers and trip times incurred on different alternative choices were evaluated during the assignment process. In this context, all travel demands were assigned to the route with the least number of transfers, while a “frequency share” rule, which was developed by Lampkin and Saalmans [8], was applied if there is at least one alternative whose trip time is within a threshold of the minimum trip time. In TRUST, total travel time of a journey with one transfer was calculated as the sum of waiting times for buses in the first and second routes, in-vehicle travel times, and a fixed transfer penalty. Note that the waiting time for a bus route was assumed to be half of the headway on the route, while the transfer penalty was 5 minutes of equivalent in-vehicle travel time. In another study by Baaj and Mahmassani [12], in which a route generation algorithm (RGA) was developed based on the framework of artificial intelligence/operations research hybrid solution approach, was also built on TRUST and its assumptions on transit

assignment problem. Chakroborty and Dwivedi [13] developed a genetic algorithm- (GA-) based solution technique to the solution of the TNDP. In the study, it was stated that, unlike previous studies concerning the route network design, an optimization tool was primarily used to minimize the reliance on heuristics. At the end of the study, a brief comparison with the results of the study by Mandl [9] and Baaj and Mahmassani [24] was provided to show the effectiveness of the proposed methodology. Szeto and Wu [14] proposed a hybrid solution method, in which GA was employed for the solution of the route design problem, while a neighbourhood search heuristic was used to search for the optimal set of frequencies. In the study, the average travel time was calculated based on the assumptions of the transit assignment in the study of Baaj and Mahmassani [11], and the proposed method was applied to the Tin Shui Wai (Hong Kong) bus network. The results showed that the total travel time could be reduced up to 23% in comparison with the current status of the Tin Shui Wai bus network. Nikolic and Teodorovic [15] solved the TNDP using the bee colony optimization (BCO) algorithm. In the study, three objective functions, which are total travel time, unsatisfied demand, and total number of buses required to meet the demand, were minimized. The transit assignment problem was solved based on the frequency share method, and the obtained results were compared with the previous models concerning the TNDP. Unlike the abovementioned studies, some researchers considered different assignment approaches. Mumford [16] assumed that the transit demand assigned to the routes with the shortest travel times and total travel time includes a constant transfer penalty and in-vehicle travel time. In the study, waiting times of users were ignored. Additionally, vehicle frequencies were not considered, and it was assumed that there were sufficient buses when solving the TNDP. Afandizadeh et al. [17] developed a GA-based model which is capable of optimizing bus assignment at depots. In the study, TNDP was formulated as a combination of user and operator costs. User costs were represented by the combination of total travel time and unsatisfied demand cost, while the operator cost included empty seat costs, dead-head trip costs, and total travel time cost. The transit assignment problem was solved based on the logit route choice model, in which waiting time was assumed to be half of the headway on the corresponding bus route. In a more recent study, Owais and Osman [18] employed GAs for the solution of the TNDP. Recently, Buba and Lee [19] applied the differential evolution approach to the solution of TNDP. In the study, the sum of total travel time and unmet demand is minimized. Ruano-Daza et al. [20] developed a global-best harmony search-based solution method for TNDP. The proposed model is applied to a real bus rapid transit system to minimize total network travel time and waste bus capacities simultaneously. Although the conventional TNDP has been considered as design of routes and setting of frequencies on a transit system, some researchers have handled the TNDP within the frequency setting, namely, the “bus scheduling” perspective. Kidwai et al. [21] presented a two-level method for vehicle scheduling. In the first level of the model, minimum service

frequencies were determined regarding the load feasibility constraint. On the contrary, the required fleet size was minimized using GA in the second level. In the study, the transit assignment problem was solved based on the procedure presented by Baaj and Mahmassani [11]. Ruisanchez et al. [22] developed a bilevel solution method for optimal bus sizes and frequencies in urban transit networks. At the upper level, a cost function representing the costs of users and operators was minimized. In the study, user cost function was formulated as a weighted sum of total transfer time, total access time, total in-vehicle time, and total waiting time. On the contrary, the transit assignment problem was solved using ESTRAUS™ traffic simulation software.

As can be seen from the literature review, the TNDP has been formulated as either both route design and frequency setting or only frequency setting in urban transit networks. Additionally, the frequency share method has widely been accepted for the solution of the transit assignment problem. It may be a reasonable approach to distribute the demand regarding the service frequencies. However, considering the exact waiting time at the origin, a transfer point may provide more realistic results instead of considering it as half of the headway since the passengers have better knowledge owing to the intelligent transportation systems and mobile applications nowadays. Doğan and Özuysal [25] state that excess waiting times in urban bus systems may lead to a change in transit users' route choice. Another widely accepted approach is the assumption of users' choice of routes with the shortest travel time. However, some users may choose some routes with longer travel times considering the level of service (i.e., comfort level and route environment), daily habits, or incomplete information. Therefore, it may be more appropriate to take the stochastic nature of users' route choice behaviour into consideration.

In this study, a bilevel simulation/optimization method is proposed to determine headways on bus routes and departure times of first buses from the beginning of the routes in urban bus networks. At the upper level, a multiobjective function representing the weighted sum of user and operator costs is minimized, while the transit assignment problem is solved using VISUM® transportation planning software at the lower level. Since headway and offset variables are integers, the TNDP is formulated as the integer programming problem, and the harmony search (HS) optimization algorithm is used for the solution. One of the novelties of our approach is the use of timetable-based assignment in which the actual transfer wait times, and the coordination of the timetable is taken into account. Moreover, by adding the offset parameter, which represents the departure time relationship between bus operations, effects of the coordination between bus operations are investigated.

Headway and departure offset optimization problem and related notations are given in the next section. Subsequently, the proposed model and the implementation of the HS algorithm are provided in Section 3. Section 4 presents some numerical applications on a medium-sized real bus network. Results and future directions are presented in the last section.

2. Problem Formulation

Effects of headways and departure times on transfer waiting time and total travel time are illustrated in Figure 1.

As can be seen from Figure 1(a), a user, who travels from the origin to destination, can directly complete his travel on Bus Line 1 (BL1). However, he may transfer to Bus Line 2 (BL2) at Stop Point (SP) to reach the destination. It can be seen in Figure 1(b) that the average speed of BL2 is higher than that of BL1. Thus, a user that boards on BL1 at 06:00 can arrive to the destination at 06:40 if he transfers to BL2 at SP; otherwise, he arrives at 06:55 via BL1. Therefore, it may be possible to reduce total travel time by transferring a faster transit line with a reasonable transfer waiting time, and each travel alternative can be called a "connection" [26]. At the second departure of BL1, there is not any transfer possibility. Thus, there is only one connection for a user who boards on BL1 at 06:55. Changes on headways and departure times of transit routes may lead to new connection alternatives or loss of some connections. Reducing headways of BL1 and BL2 provide shorter travel times for transit users. However, this leads to an undesirable situation from the operator's perspective due to the increasing fleet requirement and operational costs. Therefore, investigating the trade-off between user and operator costs is an important issue. In this section, a multiobjective optimization problem, which takes this issue into account, is proposed.

Considering the user and operator costs, the proposed optimization problem is formulated as a biobjective minimization problem as given in the following equations:

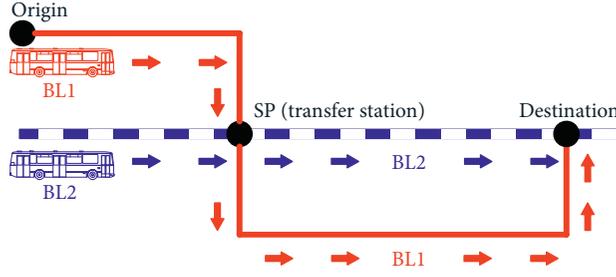
$$\begin{aligned} \min \quad Z = & D_1 \sum_{i \in O} \sum_{j \in V} \sum_{k \in G} (\text{OWT}_k^{ij} + \text{IVT}_k^{ij} + \text{TWT}_k^{ij}) \\ & + D_2 \sum_{i \in N} \left(\text{int} \left(\frac{T - \theta_i}{h_i} \right) l_i \right) + \sum_{i \in N} P_i, \end{aligned} \quad (1)$$

$$\text{subject to } h_{\min} \leq h_i \leq h_{\max}, \quad (2)$$

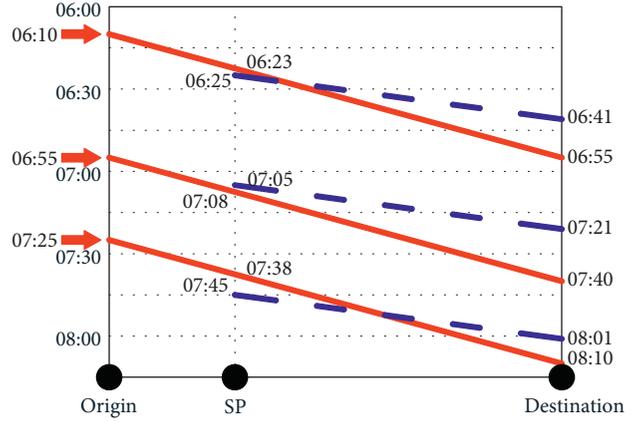
$$0 \leq \theta_i \leq h_i - 1, \quad (3)$$

$$\sum_{i \in N} \text{int} \left[\frac{t_i}{h_i} \right] + 1 \leq W. \quad (4)$$

The objective of the proposed problem is to minimize the weighted sum of the total passengers' travel time (including in-vehicle travel time and transfer wait time), total service kilometres (service km) covered by transit vehicles and a penalty term. Herein, Constraint (2) ensures that the headways on each transit route should satisfy prespecified minimum and maximum allowable values. Constraint (3) ensures that the offset of the first departure on a particular route must be less than the departure headway on the same route. Constraint (4) ensures that the required fleet size cannot exceed the available fleet size. The third term on the right side in equation (1) represents a penalty value arising from the capacity violation on routes and it is formulated as follows:



(a)



(b)

FIGURE 1: An example of (a) bus network and (b) graphical timetable.

$$P_i = \begin{cases} \phi(u_i - x_{i,\max}), & \text{if } x_{i,\max} > u_i, \\ 0, & \text{otherwise.} \end{cases} \quad (5)$$

In order to calculate in-vehicle travel time, transfer wait time, and the penalty term, which is a function of maximum passenger loads on bus routes, in the objective function given in equations (1)–(4), distribution of passengers on the transit network must be calculated, which refers to the solution of the transit assignment problem. The general assumption is that transit users choose the route with the shortest travel time between O-D pairs. However, in reality, some routes with longer travel times may be chosen by some users based on their level of service expectations, daily habits, or by incomplete information. Furthermore, some travels with one transfer between a certain O-D pair may take a shorter time than a travel with a zero transfer (or direct) transit route serving between the same O-D pair. Therefore, it may be useful to employ an approach which is closer to reality than the lexicographic strategy represented by Han and Wilson [23]. In this study, the transit assignment problem is solved based on the timetable-based assignment approach of the VISUM transportation planning tool. This approach is similar to the stochastic traffic assignment that a small part of the travel demand is assigned to suboptimal routes based on the route choice model [26]. The timetable-based assignment consists of two parts. Possible connections are investigated using the branch-and-bound algorithm at the first stage, while the passenger assignment is carried out based on a connection choice model at the second stage. The major advantages of using a timetable-based assignment are that the coordination of the timetable is taken into account by calculating the actual transfer wait times, and actual decision of the passengers can be represented realistically. Furthermore, by creating a root function, passengers can be assumed to have better knowledge of timetables. Thus, a more factual origin wait time, which has widely been taken into account as half of the mean headway in previous research, can be determined. After completing the connection search process (see [26] for details), the passenger assignment can be carried out as explained below:

The number of passengers using each bus route can be calculated based on the following equation:

$$x_i = \sum_{i \in O} \sum_{j \in D} \sum_{k \in G} q^{ij} R_k^{ij} \delta_{ik}. \quad (6)$$

Choice probability of connection k between origin i and destination j can be calculated based on the following equation:

$$R_k^{ij} = \frac{B_k^{ij-\beta}}{\sum_{k \in G} B_k^{ij-\beta}}. \quad (7)$$

Impedance of connection k in a time interval a is calculated as follows:

$$B_k^a = \text{OWT}_k^{ij} + \text{IVT}_k^{ij} + \text{TWT}_k^{ij} + \gamma v_k^{ij}. \quad (8)$$

3. Model Development

In this study, a bilevel solution model is developed for optimizing timetables in urban bus networks considering the interaction between users and operators. In the last decades, several optimization algorithms have been developed to deal with complex engineering optimization problems. Among these algorithms, genetic algorithms, simulated annealing, particle swarm optimization, ant colony optimization, and harmony search are the most popular optimization techniques [27]. In this context, the proposed model is formulated within the solution framework of the metaheuristic HS optimization technique, which has been developed by Geem et al. [28] and has widely been used to the solution of complex civil engineering optimization problems [29–35]. The HS algorithm inspires from a spontaneous performance of a musical group. In an orchestra, each musician seeks for a note that leads to the most pleasing harmony when playing together. Similarly, particular values of decision variables, which lead the objective function to reach the global optimum solution, are sought in an optimization process. According to the basic assumption

of the HS technique, a musician can improvise a note in three different ways, which are as follows:

- (i) Playing a completely random note
- (ii) Reselecting any note that he has taken in his memory by playing so far
- (iii) Selecting a note from the neighbour of a note that he has played so far

Similarly, the value of a decision variable can be determined in three ways, which are as follows:

- (i) Selecting a value chosen randomly from the possible upper and lower bounds
- (ii) Selecting a value from harmony memory
- (iii) Assigning a value in a specific neighbourhood to a value selected from harmony memory

As can be seen above, while an orchestra improvises new harmonies during a musical performance, the HS algorithm generates new solution vectors during the optimization process. In this context, the general layout of the proposed HS-based model is illustrated in Figure 2.

It can be seen in Figure 2 that the solution of the bi-objective optimization problem is carried out at the upper level, while the transit assignment problem is solved at the lower level of the proposed bilevel model. The solution

procedure of the HS-based model consists of five steps, and its stepwise flowchart is given in Figure 3.

As can be seen in Figure 3, travel demand between O-D pairs, transit network characteristics (i.e., bus routes and travel speeds), fleet characteristics (i.e., size and bus capacities), HS algorithm parameters, and a stopping criterion are presented at Step 1. There are three HS parameters governing the performance of the algorithm. The first one is harmony memory size (HMS) that represents the number of solution vectors in harmony memory (HM). Secondly, harmony memory consideration rate (HMCR) determines the probability of considering the available solutions in the HM while generating a new solution vector. The third parameter is pitch adjustment rate (PAR), which is used when the harmony memory consideration is realized and represents the probability of slightly adjusting by moving to neighbouring values of a value selected from the HM. Values of three HS parameters are also initialized at Step 1.

At Step 2, an initial harmony memory is created by generating initial solution vectors with randomly generated headway and offset values considering the preset upper and lower limits. Subsequently, the transit assignment problem is solved using VISUM for each initial solution vector to obtain passenger loads on the bus routes. Thereafter, objective function values of the initial solution vectors are calculated by equations (1)–(4) and stored as given in the following equation:

$$\left[\begin{array}{c} \text{Headways} \\ \hline h_1^1 \quad h_2^1 \quad \dots \quad h_{N-1}^1 \quad h_N^1 \\ h_1^2 \quad h_2^2 \quad \dots \quad h_{N-1}^2 \quad h_N^2 \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ h_1^{\text{HMS}-1} \quad h_2^{\text{HMS}-1} \quad \dots \quad h_{N-1}^{\text{HMS}-1} \quad h_N^{\text{HMS}-1} \\ h_1^{\text{HMS}} \quad h_2^{\text{HMS}} \quad \dots \quad h_{N-1}^{\text{HMS}} \quad h_N^{\text{HMS}} \\ \hline \text{Offsets} \\ \hline \theta_1^1 \quad \theta_2^1 \quad \dots \quad \theta_{N-1}^1 \quad \theta_N^1 \\ \theta_2^2 \quad \theta_2^2 \quad \dots \quad \theta_{N-1}^2 \quad \theta_N^2 \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ \theta_1^{\text{HMS}-1} \quad \theta_2^{\text{HMS}-1} \quad \dots \quad \theta_{N-1}^{\text{HMS}-1} \quad \theta_N^{\text{HMS}-1} \\ \theta_2^{\text{HMS}} \quad \theta_2^{\text{HMS}} \quad \dots \quad \theta_{N-1}^{\text{HMS}} \quad \theta_N^{\text{HMS}} \\ \hline \text{Solution vectors} \end{array} \right] \Rightarrow \left[\begin{array}{c} \text{Objective} \\ \text{functions} \\ \hline Z(\mathbf{h}, \boldsymbol{\theta})^1 \\ Z(\mathbf{h}, \boldsymbol{\theta})^2 \\ \dots \\ Z(\mathbf{h}, \boldsymbol{\theta})^{\text{HMS}-1} \\ Z(\mathbf{h}, \boldsymbol{\theta})^{\text{HMS}} \end{array} \right] \quad (9)$$

At Step 3, a new solution vector, which includes headway and offset variables, is generated based on HS rules in a similar manner with the improvisation of a new harmony with an orchestra. In this context, it is first decided whether a decision variable value is selected from the HM or not. This procedure is illustrated for a headway variable as follows:

$$h_i' = \begin{cases} h_i \in [h_{\min}, h_{\max}], & \text{with probability } (1 - \text{HMCR}), \\ h_i' \in \{h_i^1, h_i^2, h_i^3, \dots, h_i^{\text{HMS}}\}, & \text{with probability } (\text{HMCR}). \end{cases} \quad (10)$$

In equation (10), the value of the i^{th} headway variable in the new solution vector is either taken from the harmony memory or randomly generated between the possible value range with the probabilities of HMCR and $(1 - \text{HMCR})$, respectively. Similarly, the value of the i^{th}

offset variable in the new solution vector is determined as follows:

$$\theta_i' = \begin{cases} \theta_i' \in [0, h_i - 1], & \text{with probability } (1 - \text{HMCR}), \\ \theta_i' \in \{\theta_i^1, \theta_i^2, \theta_i^3, \dots, \theta_i^{\text{HMS}}\}, & \text{with probability } (\text{HMCR}). \end{cases} \quad (11)$$

Once the value of a decision variable is selected from the harmony memory, it is decided whether a pitch adjustment is required or not. Considering the discrete set of decision variables (i.e., successive integers), the pitch adjusting process may be performed for headway and offset variables as given in the following equations:

$$h_i' = \begin{cases} h_i' \pm \text{int}[\text{Rand}(0, 1) \times \mu], & \text{with probability } \text{PAR}, \\ h_i', & \text{with probability } (1 - \text{PAR}), \end{cases} \quad (12)$$

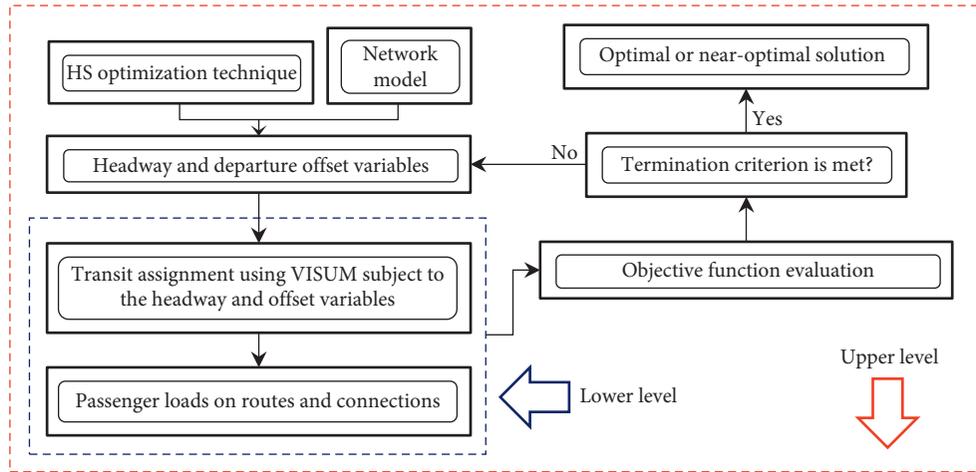


FIGURE 2: Layout of the proposed bilevel model.

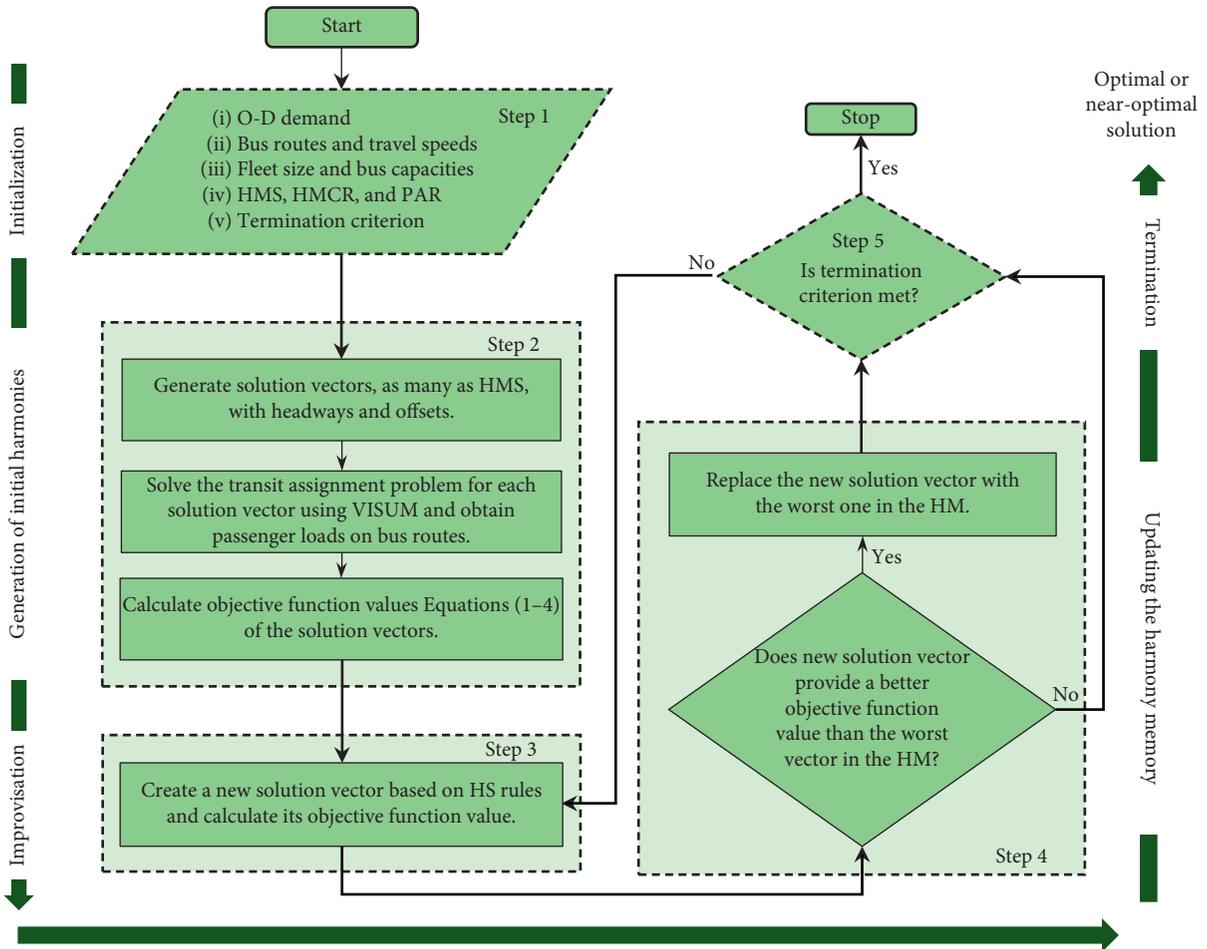


FIGURE 3: Flowchart of the HS-based model.

$$\theta'_i = \begin{cases} \theta_i \pm \text{int}[\text{Rand}(0, 1) \times \mu], & \text{with probability PAR,} \\ \theta_i, & \text{with probability } (1 - \text{PAR}). \end{cases} \quad (13)$$

Note that the procedure given in equations (10)–(13) is applied to all decision variables in the newly created solution

vector. At the end of Step 3, the transit assignment is carried out using VISUM for the new vector and its corresponding objective value is calculated by equations (1)–(4). At Step 4, a comparison is conducted between the worst solution vector in the HM and the newly created solution vector in terms of their objective function values. The one with a better objective value is kept in the HM. At the last step, the solution

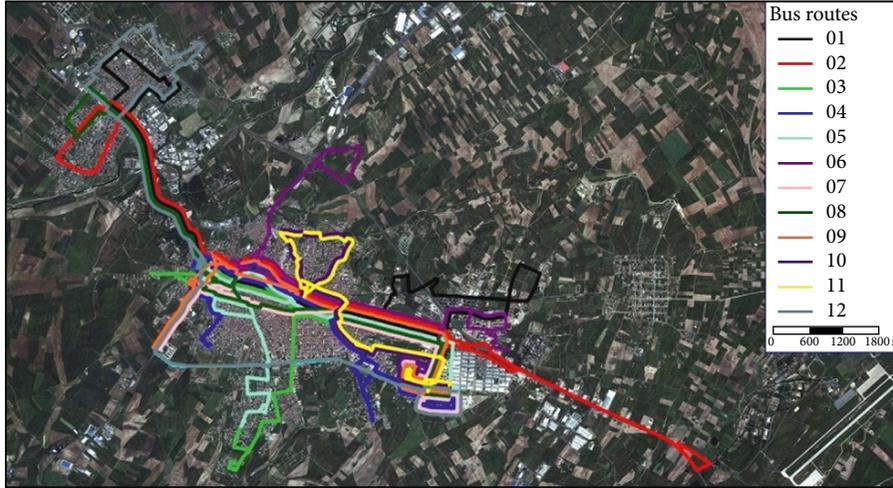


FIGURE 4: Layout of the studied bus network.

process is terminated if the termination criterion is satisfied. Otherwise, the computation is continued by iterating from Step 3 to Step 5.

4. Numerical Application

In this section, a numerical application is carried out for the bus system of the Çorlu district (Tekirdağ, Turkey) in order to evaluate the performance of the proposed model. Çorlu, located within the boundaries of Tekirdağ province, is one of the largest settlement centres in the Thrace region of Turkey after Istanbul in terms of its spatial size and trade volume. Çorlu public transportation system consists of 12 bus routes providing regular transit services. In 2017, monthly average of 2.5 million passenger trips were made with a fleet size of 80 buses with capacities of 50, 70, and 100 passengers. Layout and the lengths and vehicle capacities of the bus routes are given in Figure 4 and Table 1, respectively.

During the model computations, penalty weight is set as $\phi = 1$, impedance sensitivity is set as $\beta = 4$, transfer penalty is set as $\gamma = 5$ mins, HS parameters are set as $HMS = 100$, $HMCR = 0.85$, and $PAR = 0.05$, and band width is set as $\mu = 5$. The model algorithm is terminated after 3×10^6 iterations. Since 15% of all trips are between 07:00 and 09:00 in the morning in the Çorlu transit network, analyses are conducted for this period. Lower and upper bounds for headway variables are considered as 5 and 30 minutes, respectively. Since the objective weights D_1 and D_2 govern the trade-off between user and operator costs, the proposed multiobjective problem is solved with different weights. Owing to the vast search space of the proposed problem, Pareto efficient solutions are investigated by ignoring the offset variables, and only headway variables are taken into account. Thus, first buses on all bus routes departure at the beginning of the analysis period (i.e., 07:00 a.m.). Computational results for 11 cases with different objective weights are given in Table 2.

It can be seen in Table 2 that the total travel time is about 2217 hours for Case 1 where objective weights are $D_1 = 0$ and $D_2 = 1.0$. In the consecutive cases, where objective

TABLE 1: Lengths and vehicle capacities of bus routes.

Route code	Length (km)	Bus capacity
01	25.46	100
02	30.31	50
03	15.58	50
04	17.17	50
05	20.52	50
06	19.29	50
07	16.75	70
08	21.95	70
09	16.92	50
10	14.04	50
11	13.10	50
12	27.62	50

weight D_1 gradually increases, total travel time decreases and reaches to 2126 hours for Case 11 where $D_1 = 1.0$ and $D_2 = 0$. Meanwhile, the total service km value increases from 1311 to 1423 kilometres. This reveals that the planner fully concentrates on total service km on the transit network for $D_1 = 0$, while only the total travel time is considered for $D_1 = 1.0$. When analysing the changes in both objective values, it can be seen that the percentage decrease in total travel time is relatively close to the percentage increase in total service km values except for Case 9 where total travel time decreases about 1.4% while total service km increases about 4.1%. This indicates that a small amount of gain in cost saving for users leads to a sudden spike in operator cost. Therefore, Case 8 can be considered as the optimal solution to the proposed biobjective problem, and optimal values for the objective weights D_1 and D_2 may be considered as 0.70 and 0.30, respectively. Figure 5 illustrates the Pareto efficient solutions for both objective functions.

In Table 3, proposed headways, maximum passenger loads, and capacities on bus routes are given for objective weights $D_1 = 0.70$ and $D_2 = 0.30$. It can be seen in Table 3 that all headway values are between 5 and 30 minutes and there is no capacity violation on the transit network.

In order to investigate the effects of departure offsets in urban bus operations, the proposed problem was solved by

TABLE 2: Computational results for the proposed model without departure offsets.

Case	Objective weights		Total travel time (hour)	Total service km	Objective value	Change in the total travel time (%)	Change in the total service km (%)
	D_1	D_2					
1	0.00	1.00	2216.64	1310.88	1310.88	—	—
2	0.10	0.90	2216.64	1310.88	1401.45	0.00	0.00
3	0.20	0.80	2216.64	1310.88	1492.03	0.00	0.00
4	0.30	0.70	2212.47	1314.80	1584.10	-0.19	0.30
5	0.40	0.60	2206.81	1319.79	1674.60	-0.26	0.38
6	0.50	0.50	2199.70	1325.25	1762.48	-0.32	0.41
7	0.60	0.40	2191.76	1330.84	1847.39	-0.36	0.42
8	0.70	0.30	2177.95	1344.00	1927.77	-0.63	0.99
9	0.80	0.20	2147.70	1402.21	1998.60	-1.39	4.33
10	0.90	0.10	2127.55	1421.45	2055.54	-1.02	1.52
11	1.00	0.00	2125.76	1423.48	2125.76	0.00	0.00

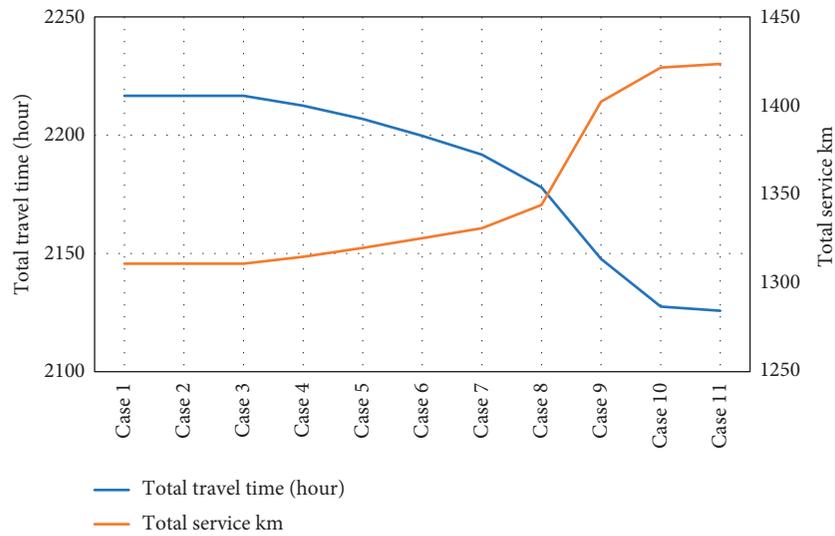


FIGURE 5: Pareto efficient solutions for both objectives.

TABLE 3: Proposed headways and their corresponding maximum load and capacity values.

Route code	Headway (minutes)	Maximum load (no. of passengers)	Capacity
01	21	413	500
02	14	439	450
03	29	217	250
04	24	299	300
05	19	337	350
06	23	276	300
07	16	489	490
08	26	234	250
09	30	194	200
10	29	97	200
11	30	108	200
12	30	72	200

considering both headway and offset variables for objective weights $D_1 = 0.70$ and $D_2 = 0.30$. Convergence history of the solution process is illustrated in Figure 6.

It can be seen in Figure 6 that the model algorithm achieves a steady convergence after about 1.2×10^6 iterations.

In order to illustrate the robustness of the proposed approach, the model was run 100 times with different initial solutions and random seeds. After the analyses, minimum, maximum, and average objective function values are obtained as 1901.87, 1920.28, and 1904.45, respectively. While the minimum objective function value was reached with 55% of all runs, standard deviation was calculated as 4.54. Computational results for the proposed model are given in Table 4.

It can be seen in Table 4 that the total travel time is about 2287 hours for the current bus network of Çorlu. It can also be seen that the headway optimization leads to a decrease of about 4.8% while both headway and departure offset optimization can reduce total travel time of about 5.4% in comparison with the current bus network. On the contrary, total distance covered by buses can be reduced about 9.8% by optimizing the headways on bus routes. Moreover, considering different departure times for the first buses on bus routes may reduce this value about 13.3%. In Table 5, comparison between the current and proposed bus networks is provided in terms of headway and capacity values. Additionally, departure offsets with

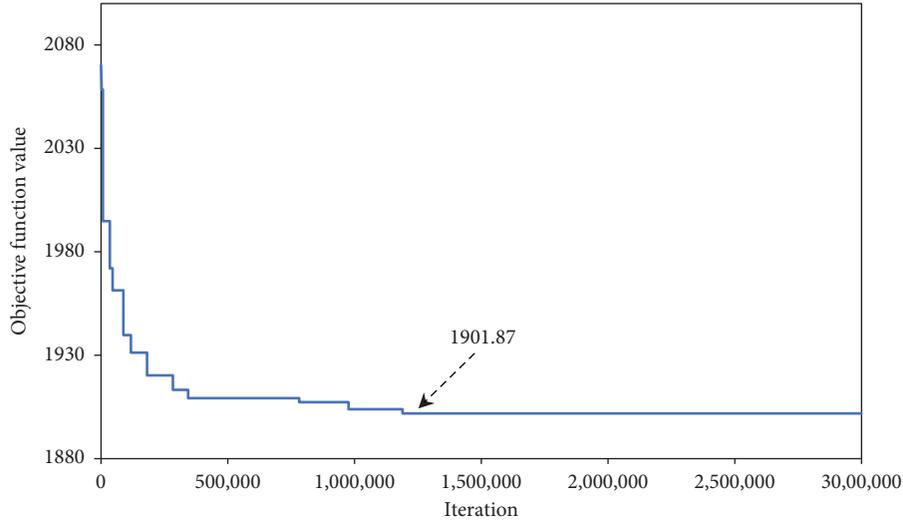


FIGURE 6: Convergence history of the proposed model with headway and offset variables.

TABLE 4: Computational results in comparison with the current bus network of Çorlu.

Case	Total travel time		Total service km	
	Value (hour)	Improvement (%)	Value (km)	Improvement (%)
Current bus network	2286.64	—	1490	—
Bus routes with optimal headways	2177.95	4.75	1344	9.80
Bus routes with optimal headways and departure offsets	2163.67	5.38	1291	13.36

TABLE 5: Model results.

Route code	Current bus network				Model results			
	Bus capacity (no. of passengers)	Headway (minutes)	Capacity (no. of passengers)	Headway (minutes)	Departure offset (minutes)	Maximum load (no. of passengers)	Capacity (no. of passengers)	
01	100	11	1100	21	0	413	600	
02	50	11	550	14	0	430	450	
03	50	15	400	27	16	200	200	
04	50	13	500	22	7	298	300	
05	50	15	400	17	1	354	400	
06	50	17	400	23	0	291	300	
07	70	15	560	18	9	477	490	
08	70	24	350	25	23	249	280	
09	50	24	250	30	12	184	200	
10	50	30	200	30	13	94	200	
11	50	30	200	25	5	137	250	
12	50	30	200	30	24	49	200	

their corresponding maximum passenger loads on bus routes are given for objective weights $D_1 = 0.70$ and $D_2 = 0.30$. It can be seen in Table 5 that all headway values are between 5 and 30 minutes, all departure offset values are between possible bounds, and there is no capacity violation on the bus network according to the model outputs.

Number of trips observed for the current bus network and those calculated based on the proposed model are given in Table 6.

As can be seen in Table 6, 2934 and 169 trips are made with one and two transfers, respectively, during the analysis period on the current bus network of Çorlu. When optimal

headways are applied to the bus routes, the number of trips with both one and two transfers can be reduced up to 2461 and 116 trips, respectively. This reveals that the number of users that can complete their travels on a particular bus route can be increased by headway optimization. On the contrary, when optimal departure offsets are considered, the number of trips with one transfer increases in comparison to the bus network only with optimal headways. This increase indicates that optimal departure offsets may provide a coordination of bus services and shorter transfer wait times resulting in a reasonable reduction in total travel time and total distance covered by buses.

TABLE 6: Number of trips for the current bus network and modelling results.

Case	Number of trips		
	Without transfer	With one transfer	With two transfers
Current bus network	11234	2934	169
Bus routes with optimal headways	11488	2461	116
Bus routes with optimal headways and departure offsets	11456	2537	104

5. Conclusions

In this study, a multiobjective minimization problem, which was formulated as a weighted sum of total travel time of transit users and total distance covered by transit vehicles, was proposed. Subsequently, a bilevel simulation/optimization model was developed to optimize departure headway and offset variables in urban bus networks. At the upper level of the model, the proposed problem was solved based on the HS optimization algorithm solution framework. On the contrary, the transit assignment problem was solved using the timetable-based assignment approach of VISUM transport planning software at the lower level.

Owing to the multiobjective nature of the problem, investigating the trade-off between user and operator benefits is an important issue. In this context, the proposed model was first applied to a real-life transit network with different weights in order to analyse Pareto efficient solutions and determine the optimal values of objective weights. Those computations were made by ignoring departure offset values that require more computational efforts due to the vast search space of the multiobjective problem. It was found that the total travel time and total service km could be reduced by 4.8% and 9.8%, respectively, compared with the current bus network. Once the optimal values of the objective weights were determined, the proposed model was applied to the network by considering both departure headway and offset variables. The results showed that 5.4% and 13.3% improvements could be achieved by including departure offset variables in the model.

Fleet constraint considered in the proposed model ensures that the number of buses required on particular routes does not exceed the number of buses allocated to those routes. In future, a bus allocation algorithm will be integrated into the proposed model that can distribute a common fleet including buses with different types and capacities. Integrating a route construction algorithm into the proposed model is considered as another future direction.

Abbreviations

Sets/indices

- N : Set of routes in the transit network
- O : Set of origins
- V : Set of destinations
- G : Set of connections
- i, j, k : Indices

Parameters

- IVT_k^{ij} : In-vehicle travel time on the connection k between origin i and destination j
- OWT_k^{ij} : Origin wait time on the connection k between origin i and destination j
- TWT_k^{ij} : Transfer wait time on the connection k between origin i and destination j
- l_i : Length of route i
- P_i : Value of the penalty arising from the capacity violation on route i
- T : Length of the analysis period
- h_{\min} : Minimum headway
- h_{\max} : Maximum headway
- t_i : Single trip time of route i
- W : Available bus fleet size
- x_i : Number of passengers on route i
- $x_{i,\max}$: Maximum passenger load on route i
- u_i : Vehicle capacity of route i
- ϕ : Penalty weight
- R_k^{ij} : Choice probability of connection k between origin i and destination j
- δ_{ik} : Element of route/connection incidence matrix that $\delta_{ik} = 1$ if connection k uses route i , and $\delta_{ik} = 0$ otherwise
- β : Parameter for modelling the impedance sensitivity
- B_k^{ij} : Impedance of connection k between origin i and destination j
- B_k^a : Impedance of connection k in a time interval a
- μ : Arbitrary band width
- $\text{Rand}(0, 1)$: Uniform random number between 0 and 1
- v_k^{ij} : Number of transfers on connection k between origin i and destination j
- γ : Transfer penalty
- q^{ij} : Travel demand between origin i and destination j
- D_1 : Weight for the total travel time
- D_2 : Weight for the total service km

Decision variable

- h_i : Departure headway on route i
- θ_i : Departure offset for the first bus on route i .

Data Availability

The data used to support the findings of this study may be released upon application to the Metropolitan Municipality of Tekirdağ, which can be contacted at tbb@tekirdag.bel.tr.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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