International Journal of Engineering &Technology, 13 (2) (2024) 372-379

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

ODSTP: a single-objective model for optimizing school transport in sub-Saharan African metropolises

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Abstract

The density of road traffic in large cities in sub-Saharan Africa causes enormous inconvenience to pupils and students, including numerous late arrivals at school and a general state of stress leading to poor school results. In this work, we propose a single-objective optimization model based on a transport-on-demand approach, taking quality of service into account. Our model has the advantage of minimizing both the total tour distance, the tour duration and the route cost (the sum of the fixed vehicle cost and the running cost). To solve our problem, we use a meta-heuristic: the tabu search method.

Keywords: *Education; Transport; DARP; VRP; Optimization.*

1. Introduction

School transport is a major issue for the metropolises of sub-Saharan Africa, where rapid population growth and galloping urbanization [1] exacerbate the challenges associated with mobility. In this context, the quality of education is often hampered by inadequate transport infrastructure, but above all by inefficient transport management systems. As a result, pupils and students in these large cities are frequently confronted with long commutes that are detrimental to their attendance and performance at school.

To combat this problem, various solutions have been implemented by public authorities, school managers and some transport service providers. These initiatives range from increasing the fleet of vehicles dedicated to student transport to reorganizing student timetables. However, these measures do not address the problem holistically and lack effectiveness, as they lead to other difficulties, including increased greenhouse gas emissions and worsening traffic congestion. Moreover, traditional approaches to transport planning often prove ill-adapted to the specificities of African urban environments, where economic, social and geographical constraints are particularly marked.

Optimizing school transport therefore appears to be an imperative necessity to guarantee improved school results. In this context, an on-demand transport optimization model adapted to the context and taking into account cost minimization or journey time reduction can offer a pragmatic and targeted solution. According to Toth et al [2], computerized systems using optimization techniques can generate savings of 5% to 20% on transport costs.

The structure of this article is as follows: we begin by examining the negative impact of urban mobility problems on students' academic performance. Next, we will provide a formal description of DARP, focusing particularly on learner transport in sub-Saharan Africa. Then, after presenting some research work in this field, we will outline our methodology and contribution. Finally, we conclude with a discussion of the results obtained and a summary of the points raised.

2. Impact of students' urban mobility problems on their academic performance

In Africa, many large cities are characterized by high population density, which creates major urban mobility problems. Pupils and students are particularly hard hit by this situation. The modernization of infrastructure and road transport systems has not always kept pace with demographic growth, making it difficult for students to get to and from school every day.

As a result, there is a decline in performance among these learners, particularly those in the observation cycles. This is due to late arrivals at school, long waits at stops and during the journey, as well as the anxiety and stress associated with transport. These problems can lead to a deterioration in the learner's general state of mind, and even to nervous imbalance, preventing him or her from concentrating on the course in class.

One study [3] divided the symptoms of psychosomatic disorders experienced by students subjected to long school bus journeys into three categories. These are:

- Deterioration in general condition, due in particular to lack of sleep and fatigue caused by long journeys.
- Reduced resistance to illness, partly due to exposure to the elements while waiting for transport.

- disturbances of attention, memory, personality, emotionality, agitation, anxiety, apathy, etc.

Such a situation is conceivable, especially for a pupil who used to take around five to ten minutes to get to elementary school and who, now in 6th grade, has to make a home-school journey of over an hour, covering several dozen kilometers. Added to this are the difficult transport conditions (traffic jams, long waits, discomfort of the bus, etc.). As a result, as a young teenager, he or she has to put up with a daily commute of several hours in addition to the long hours of school. Transport routes are often poorly organized and don't always fit in with the school and university calendar, leaving students little time for a good night's sleep, forcing them to get up very early in the morning and often come home late at night. When they return home, the accumulated fatigue prevents them from revising their lessons effectively. This cycle repeats itself every day of the week. Under such conditions of mobility, it is inevitable that this contributes to a drop in school performance, or even failure.

3. The dial-a-ride problem (DARP) and its application to student transport in sub-saharan africa

3.1. Some work on DARP

The Dial-a-Ride Problem (DARP) is a complex NP-Hard problem at the intersection of logistics, operations research and combinatorial optimization. It is particularly relevant in the context of on-demand transportation services, where users can request specific routes at given times. First introduced in the 1970s in northern countries, DARP involves designing routes for vehicles to meet a variety of passenger transport demands [4], while guaranteeing a high quality of service to passengers that minimizes tour costs (distance travelled, service time, number of vehicles used) and environmental impact. In this type of transport, customers (passengers) submit a request to an operator, specifying the pick-up point (point of departure), the final destination, the number of people to be transported and the desired time slot. DARP offers a better quality/cost ratio. DARP can be operated in either static or dynamic mode. In static mode, all transport requests are recorded in advance, enabling efficient optimization of the problem. In dynamic mode, on the other hand, requests are revealed progressively, and routes are adjusted in real time to incorporate these new requests.

Research into solving static DARP with multiple vehicles includes the work of (Cordeau and Ropke, 2006) [5]. The authors proposed two exact branch-and-cut algorithms, formulating the problem as a linear integer program. The relaxation of certain constraints is initially used to solve the model. They used an instance of 36 requests and 96 requests respectively for the first and second algorithms.

(Kumar and Panneerselvam, 2017) [6] have developed an efficient genetic algorithm for the vehicle touring problem with time windows. The aim of this research is to solve problems related to traffic jams, which cause unnecessary delays and thus result in significant customer and revenue loss for companies. Thus, the authors propose a genetic algorithm (GA) to optimize vehicle routing under time constraints while minimizing the total distance covered and the number of vehicles required, and propose alternative routes to avoid congested areas

(Diaby et al, 2020) [7] have proposed a DARP model adapted to the public transport of “wôrô wôrô” cabs in sub-Saharan Africa. These cabs transport groups of people without any affinity, from point A to point B without stopping. To solve this problem, the authors proposed an exact solution based on a mixed integer program (MIP).

Finally, (Ferreira et al, 2021) [8] proposed a hybrid optimization algorithm to provide a solution to a bi-objective green vehicle routing problem (BGVRP) applied to a newspaper distribution. Their methodology, illustrated with a newspaper distribution case study and Instances from the literature, resulted in an optimization of 19.9% for Objective Function 1 (OF1; minimization of CO_2 emissions and minimization of total distance) and 87.5% for Objective Function 2 (OF2; minimization of demand difference).

The research mentioned above is not sufficiently adapted to the case of school transport in sub-Saharan Africa, where other means of transport come into play. These include communal cabs called “woro-wôro” and mini-buses called “Gbaka”, which are still used by pupils and students in large sub-Saharan cities such as Abidjan in Côte d'Ivoire, and which are characterized by a fairly disorganized system. Although the work of (Diaby et al, 2020) focuses on the wôrô-wôrô communal cab system in Abidjan, it does not take into account the optimization of trip costs, i.e. the sum of the fixed cost of the vehicle and the cost of driving. In addition, their model was solved using an exact method, which is limited for large instances.

3.2. DARP applied to the transport of pupils and students in sub-saharan africa

Pupils and students in the major cities of sub-Saharan Africa, notably Abidjan in Côte d'Ivoire, can be grouped according to two main modes of transport:

- Individual commuters: they generally live close to their school and travel to school on foot, bicycle or motorcycle, or are driven by a parent in a car. In addition, we are seeing an increase in requests for transport via apps such as Yango.
- Commuters: The largest group. These individuals take advantage of pick-up services, which may be specially organized or integrated into regular public transport routes:
- Organized transport is generally:
- The school may decide to set up a transport service using its own fleet of coaches or minibuses, which it distributes in the main towns of the city to pick up its pupils, in return for a monthly, annual or even weekly subscription.
- Through a service provider who offers its transport solutions to schools, providing them with various means of transport such as such as buses, minibuses or private vehicles.
- Or on the initiative of parents who get together to hire a vehicle or minibus to transport their children, generally as part of a as part of a car-sharing scheme.
- Transport with regular public transport routes comes in several types, but their objective remains the same: to move users, without distinction, from point A to point B. This category includes:
- Buses: Public bus networks are one of the most widespread means of public transport in sub-Saharan Africa. These include SOTRA in Abidjan, SONUTRI in Niamey, Bamabus or Tababus in Bamako, and SOTRACO in Ouagadougou. These services follow predefined routes and regular schedules, making it easy for passengers to get from one place to another.
- Other modes of public transport: This includes coach or bus services, minibuses (called Gbaka in Abidjan or dala dala in Dar es Salaam), as well as vehicles, collective taxis or VTCs (like the “wôrô-wôrô” in Abidjan, and in certain regions, motorcycle taxis or tricycles, such as the “salonnis” in several West African capitals). These transport services, managed by numerous owners, are operated with a view to lucrative, where providers seek to maximize revenue while reducing operating costs. To achieve this, they implement various strategies, such as adjusting their routes based on high demand areas (especially during peak hours), waiting for

enough customers before leaving ("full and go" system), and avoiding urban areas where the roads are in poor condition in order to limit maintenance costs.

This transport system, although more economical [9], undoubtedly causes many inconveniences for the populations, especially for students and students who must adhere to strict course schedules. Figure 1 below illustrates the ecosystem of services related to student transportation demand in major cities in sub-Saharan Africa. Our approach to solving the Student-on-Demand Public Transit problem is known as ODSTP (On-Demand Student Transportation Problem).

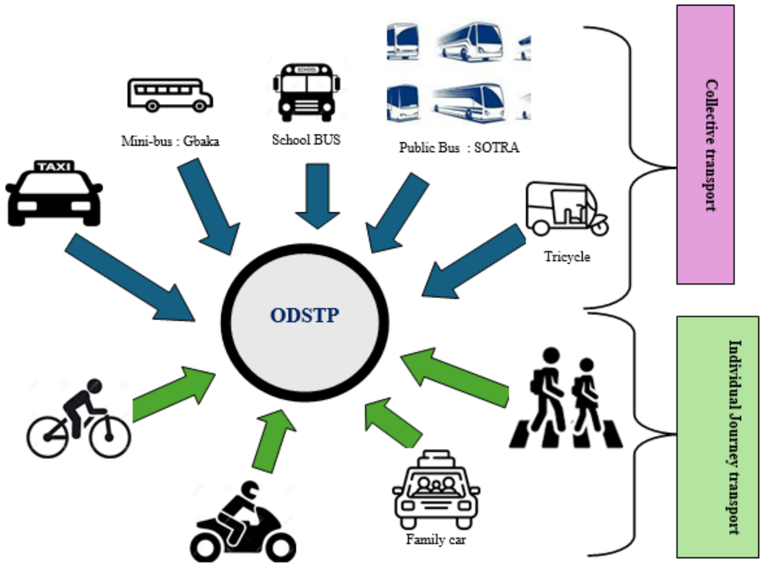

Fig. 1: Ecosystem of Student Transport Demand Services in Sub-Saharan Cities.

Faced with the coexistence of several modes and types of transport (artisanal and informal or professional and regulated), not meeting the same regulatory criteria and leading to a degradation of service quality and unfair competition between operators, it is important to propose innovative solutions for optimizing transport in these large cities.

In this work, we look at the transport format for collective journeys, whether organized or not.

4. Modeling our on-demand student transportation approach (ODSTP)

In our approach, we aim to improve the transportation of pupils and students in order to significantly reduce costs for the various players (fixed costs linked to vehicles and operating costs). More specifically, our model will help transport service providers or vehicle owners to optimally allocate students to vehicles, while enabling them to plan the most efficient routes for each vehicle, in order to avoid waste of resources. This optimization will also inevitably help to reduce environmental pollution by cutting CO_2 emissions.

In this approach, the aim is to reduce travel time, distance covered and the cost of vehicle rounds. For our problem, illustrated in figure 2 below, we consider a service provider (company, individual or institution) with a heterogeneous fleet of vehicles (buses, minibuses, Gbaka, cabs, etc.) parked in a depot (depot 0). This service provider is responsible for collecting pupils and students from various stops. Pupils request transport from their stop, specifying the desired time window and destination. The aim is to minimize travel time, distance and the cost of vehicle rounds.

The transport service provider's task is to schedule the requested rounds, ensuring the best allocation of vehicles to the requests so as to minimize the various costs in terms of distance, time, fixed vehicle costs and running costs. To do this, we have N_E pupils or students to transport and N_K vehicles. Each student represents a transport request or demand and is associated with two vertices: a departure point and a destination point. A tour is carried out by a vehicle departing from the depot (point 0) for the school (point 7 or 8 on fig. 2) and finishing back at the depot. Each tour must obey a certain number of conditions or constraints, in particular:

- Compliance with time windows $[a_i,b_i]$ for pick-up and drop-off $[a_{i+n},b_{i+n}]$ of requests.
- Vehicle capacity.
- All transport requests are satisfied.
- Maximum tour duration.
- Travel time for each student.
- The order in which the vehicle passes through the stops.
- The transporter has a limited fleet of vehicles.

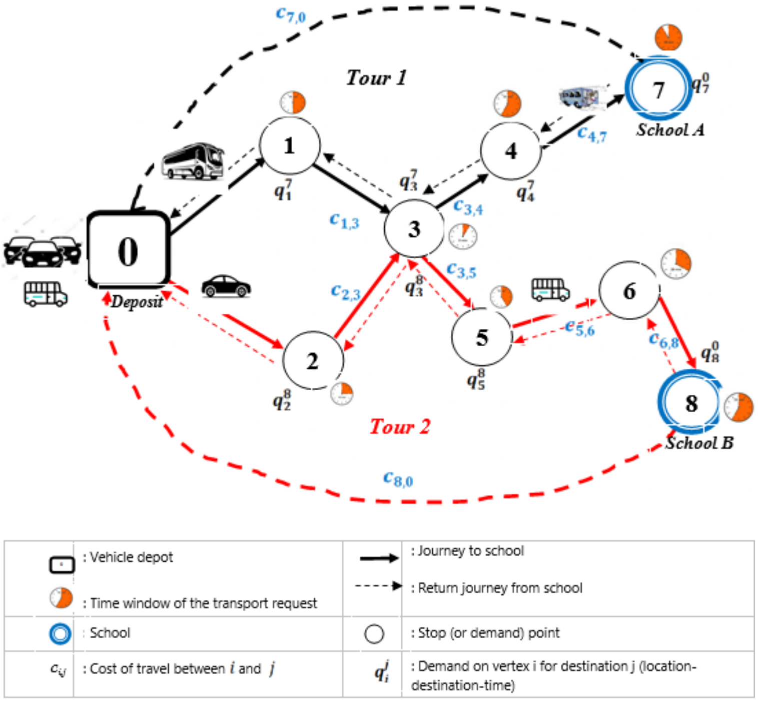

Fig. 2: Modeling Example of Our ODSTP (On-Demand Student Transportation Problem) with 2 Vehicles and 9 Vertices Including A Depot

In our approach, satisfying a transport request involves the service provider picking up a number n_i and n_j of pupils at stops i and j, who have chosen the same destination and the same time window (within the limit of available places), and dropping them all off at the same destination i+n.

The number of people picked up at the various stops must be equivalent to the number of people at destination i+n (at the school) :

$\sum n_i = n_{i+n}$

According to this principle, people from the same stop with different destinations or different time windows cannot be on the same tour.
So :

- i and j, points representing the individuals (or students) to be transported.
- R, all students pick-up points.
- Γ, all points of descent for pupils and students (i.e. schools);
- ϴ, all vehicle depots;
- nD, number of deposits ;
- K, all fleet vehicles;
- G = (M, A), a complete directed graph with:
- M, the whole including the vehicle depot(s) as well as the student pick-up and drop-off points i, j. (M = R U Γ U ϴ)
- A , all the paths or arcs between two points i and j (i, j) ∈ A
- Nk, the number of vehicles at the depot.
- n_s^k, number of vertices covered on the tour of vehicle k, including the depot.
- Ck, the capacity of the vehicle k;
- ci,j , cost of the route between i and j;
- m, the number of rounds of the problem solution S;
- S, a solution to the problem. S consists of m rounds {t1, t2 ,…, tm } with tk , the kth round of the solution | k=1,…, m
- Tk, all routes that can be covered by vehicle k ;
- [ai,bi] the time window for picking up the i request.
- [ai+n,bi+n], the time window for passengers to disembark at destination.
- tij, the shortest path between i and j;
- dij , the distance between the vertices i and j;
- q_i^j ,The demand on the top i for destination j: a client is characterized by its location (i), its destination (j) and the time interval [ai,bi] during which it can be visited and picked up ;
- ζ_{ij}^k , the decision variable ;
- ζ_{ij}^k = 0, if vehicle k is travelling i-j and equal to 0 otherwise.
- t_i^k, time of arrival of the vehicle on the top i of the k-tour.
- h_i^k, vehicle start time k on top i;
- d_i^k, time of departure of the vehicle from the top i of the tour k;

Objective Function:
The mathematical formulation of the Objective Function of our on-demand student public transportation problem (ODSTP) is as follows:

$$F = \min_{t} \sum_{\substack{k=1 \\ k\in K}}^{m} \left(\sum_{\substack{i=1 \\ i,j\in \mathcal{M}}}^{n_s^k-1} \left(c_{i,j} + t_{ij} + d_{ij}\right) \zeta_{ij}^k \right) \tag{1}$$

According to the following constraints:

- C1 : All the transport requests are satisfied ;

$$\sum_{\substack{k\in K \\ j\in \Gamma \cup \Theta}} \zeta_{ij}^k = 1 \text{ , } \forall i \in \mathrm{R} \tag{2}$$

- C2 : The load of the vehicle must never be greater than its maximum capacity

$$\sum_{i\in \mathrm{R} \cup \Gamma} n_i \leq C_k \tag{3}$$

- C3 : The start date of service on a summit i is between its arrival and departure date

$$t_i^k \leq h_i^k \leq d_i^k, \forall i \in \{1,.,n_s^k\} \tag{4}$$

- C4 : The arrival time at a pickup node is always less than that of the destination node

$$t_i^k + t_{i,n+1} \leq t_{n+1}^k \text{ , } \forall i \in \mathrm{R} \tag{5}$$

- C5 : Time windows must be respected

$$a_i \leq h_i^k \leq b_i \text{ , } \forall i \in \mathrm{R} \cup \Gamma \tag{6}$$

- C6 : Ensures consistency of each route and the prohibition of sub-tours.

$$h_i^k + t_{i,j} - M\left(1 - \sum_{k\in K} \zeta_{ij}^k\right) - h_j^k \leq 0 \text{ ; } \forall (i,j) \in \mathcal{M}; i,j \notin \Theta \tag{7}$$

5. Algorithm for solving our ODST problem

We have chosen Taboo Search as the method for solving our model, because of its effectiveness in combinatorial optimization and also because it allows solutions to be memorized as the search progresses, thus enabling a good exploration of the search space. Furthermore, its choice is motivated by the deterministic aspect of its method of accepting candidate solutions, unlike other conventional metaheuristics, and also by the fact that this algorithm is characterized by a reduced computation time, hence its adaptation to the dynamic environment. Below is the pseudo-code for solving our model.

Pseudo-code

```
1.    Initialization :
a.    Randomly generate an initial solution So
b.    Define maximum number of iterations N_max
c.    Set size t_max of Tabou list (Γ)
d.    S ← So
e.    S* ← So  // S* is the best solution encountered
f.    C* ← F (So) // C* is the cost of solution S* and F is the Objective Function
g.    Γ ← ∅
h.    i ← 0 // current iteration
2.    while i < N_max  do
3.            Generate a subset V(S_k) of solutions in the neighborhood of solution S_k
4.    Choose in V(S_k) the movement S'_k such as ∀S ∈ V(S_k), F(S) ≥ F(S'_k ) et S'_k ∉ Γ
5.            S_k+1 ← S'_k
6.            If Γ is full (t_l = t_max) then
7.                    Replace the last element of Γ with S_K+1
8.            If no
9.                    Add S_K+1 to Γ
10.   i++
11.           End If
12.           If (F(S_k+1) < C*) then
13.                   S* ← S_k+1 and C* ← F(S_k+1)
14.           End If
15.   End of algorithm
```

6. Materials and methodology

The choice of good instances is important for model validation. In our current work on student-demand transit in sub-Saharan Africa (ODSTP), we used the same instances as (Diaby et al, 2020) in their research work on the 2WDTP model for applying the DARP in Saharan

countries: the case of the so-called "woro-woro" communal taxis. This choice was made in order to better compare the effectiveness of the two models: ODSTP and 2WDTP. These instances were generated by them, from an algorithm of generation of instances adapted to the problem treated. This instance generation algorithm relies on several input parameters, such as the axis and length of the ordinates of the routing area. It is used to design a repository (OIJ) in which a set of requests is randomly generated, taking into account drop-off and pick-up nodes, as well as load requests. Based on the number of requests, the authors also determine the number of vehicles required, taking into account depots and associated capacities. Then, the travel time and Euclidean distance for each arc are calculated.
The generated instances include a reasonable number of requests R ($05 \leq R \leq 16$), a heterogeneous number K of vehicles ($02 \leq K \leq 07$) and a number n_D of deposits ($01 \leq n_D \leq 04$).
We carried out our experiment on a Surface Pro 9, 64-bit computer with an Intel(R) Core(TM) i7-1065G7 CPU @ 1.30GHz 1.50 GHz, 16.0 GB RAM,

7. Results and discussion

In this contribution, we have chosen to compare the effectiveness of our ODSTP school transport optimization approach with the 2WDTP approach of (Diaby et al, 2020) in terms of CPU execution time, travel time and total distance covered per instance.
Table 1 below shows the different results obtained by the two approaches (ODSTP and 2WDTP) applied to the instances described above. Instances are grouped according to the number of requests. Nodes do not have the same configuration.

Table 1: Comparative Results Between Our ODSTP Approach and That of (Diaby Et Al, 2020)

Instance name					CPU execution time (s)		Distance traveled		Travel time (min)	
Noms	R	N	K	n_D	2WDTP	ODSTP	2WDTP	ODSTP	2WDTP	ODSTP
R_{1a}	05	10	02	02	0,030	0,035	225,44	239,18	341,08	253,26
R_{1b}	05	10	02	01	0,002	0,003	302,05	350,56	320,74	378,19
R_{1c}	05	10	02	02	0,030	0,041	218,49	214,60	538,42	409,14
R_{1d}	05	10	02	02	0,010	0,015	324,12	406,52	632,04	523,30
R_{1e}	05	10	02	01	0,020	0,023	260,09,	333,45	540,28	518,16
R_{2a}	07	14	04	03	0,080	0,081	506,14	425,28	625,67	594,05
R_{2b}	07	14	04	03	0,110	0,090	496,24	557,10	754,10	608,92
R_{2c}	07	14	04	03	0,133	0,095	620,32	605,07	1233,60	818,12
R_{2d}	07	14	04	04	0,112	0,090	494,65	475,16	885,18	702,03
R_{2e}	07	14	04	03	0,310	0,122	828,44	696,25	990,57	812,33
R_{3a}	10	20	04	03	6,890	3,250	1015,27	904,65	1450,38	1040,55
R_{3b}	10	20	04	02	2,282	1,561	1425,30	1267,02	1173,10	991,87
R_{3c}	10	20	04	03	0,360	0,110	920,34	776,20	1230,70	1076,98
R_{3d}	10	20	04	03	7,733	3,982	2026,13	1902,80	1603,45	1115,14
R_{3e}	10	20	04	03	4,830	2,015	1938,14	1818,39	1305,23	1079,14
R_{4a}	13	26	05	03	16,590	10,701	3150,22	2428,85	1911,62	1612,30
R_{4b}	13	26	05	03	131,631	80,955	3678,68	3490,44	2105,44	1722,38
R_{4c}	13	26	05	04	90,840	75,012	3501,45	3425,39	2860,84	1812,21
R_{4d}	13	26	05	04	233,022	114,667	3753,69	3512,16	3223,42	1944,31
R_{4e}	13	26	05	04	11,750	07,010	3160,08	2918,10	2889,56	1880,01
R_{5a}	16	32	07	04	284,064	194,671	4326,41	3890,33	3145,67	2034,90
R_{5b}	16	32	07	04	871,331	597,880	4534,87	4021,13	3468,20	2522,12
R_{5c}	16	32	07	02	3601,520	2003,760	4701,90	4123,67	3026,44	2860,50
R_{5d}	16	32	07	04	21,060	12,108	3144,18	3025,17	3510,13	3017,98
R_{5e}	16	32	07	04	1219,281	714,097	4567,88	3235,54	3866,54	3160,11
Total					6504,021	4322,374	50120,52	45043,01	43632,4	33488

Figure 3 compares the efficiency of our approach in terms of execution time with that of (Diaby et al, 2020).

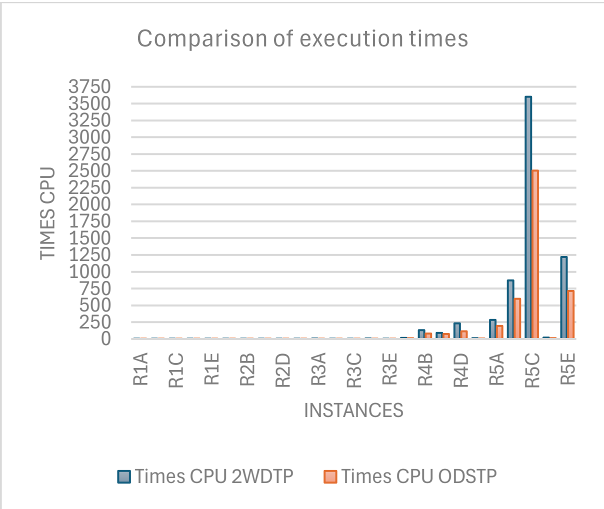

Fig. 3: Comparison of Execution Times Obtained by Our Approach and That of (Diaby Et Al, 2020).

The analysis of these results shows the effectiveness of our ODSTP approach in terms of execution time compared to the 2WDTP approach of (Diaby et al, 2020), especially for large-scale instances. However, looking at the results table, it can be seen that for small size instances (R_{1a}, R_{1b}, R_{1c}, R_{1d}, R_{1e} and R_{2a}), the approach of (Diaby et al, 2020) gives a better time than ours.

Figure 4 compares the two models (ODSTP and 2WDTP) in terms of distance travelled.

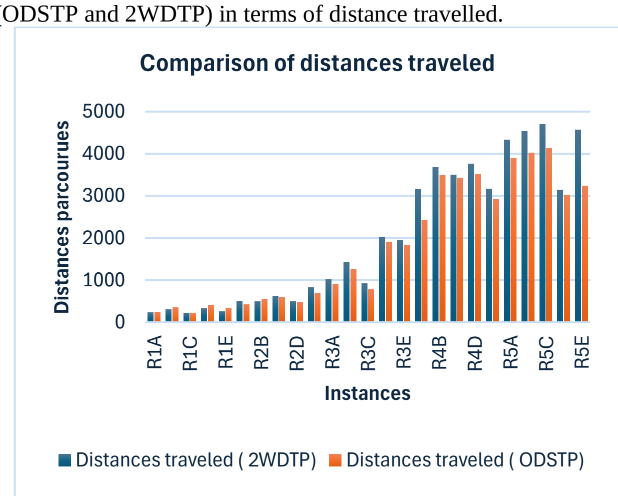

Fig. 4: Comparison of Distances Travelled by Both ODSTP and 2WDTP Approaches.

It is also easy to notice, according to figure 5 that if we take out instances R_{1a}, R_{1b}, R_{1d} and R_{1e}, our ODSTP approach minimizes the total distance of the tours.
Finally, in Figure 5, we present the comparison of our results in terms of total tour duration according to our ODSTP approach and the 2WDTP approach (Diaby et al, 2020).

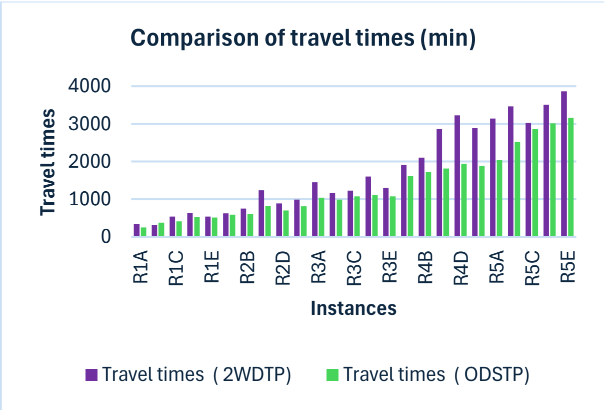

Fig. 5: Comparison of Travel Time by Both ODSTP and 2WDTP Approaches.

The analysis in Figure 5 shows the effectiveness of our approach in terms of optimizing tour travel time compared to the approach of (Diaby et al, 2020). This effectiveness is more pronounced for larger instances. Ultimately, according to the various results obtained, our approach is effective compared to that of (Diaby et al, 2020), particularly for large instances. Indeed, it minimizes most the distance and travel time of the rounds and also gives a better execution time. Thus, solving our model for optimizing the collective transport of schoolchildren in large cities in sub-Saharan Africa with the Tabou search metaheuristic has the merit of improving the punctuality of learners and consequently school results, by enabling the reduction of school travel times and distances.

8. Conclusion

Mobility of students in the major cities of sub-Saharan Africa is a great challenge, as it can have negative consequences on their academic performance. This problem is of particular interest to transport service providers, governments, school administrators and students in large cities. In this study, we developed a single-objective model for optimizing on-demand transportation adapted to school transport, which we named ODSTP (On-Demand Student Transportation Problem), in order to contribute to the improvement of educational outcomes in these cities. There is not enough research on school transport-specific VRP, which remains a disorganized field in Africa. Our system directly influences the quality of service offered to users and specifically to students in the major sub-Saharan cities by minimizing time and distance between home and school but also travel costs (sum of the fixed cost of the vehicle and the running cost).
To solve our problem, we used a meta heuristic, namely Tabou search, due to the complexity of this problem. We obtained quite interesting results in comparison with the results obtained by other methods, notably those of Diaby et al.
For the continuation of our work, we initially plan to hybridize our tabu search algorithm with other meta-heuristics, such as simulated annealing because of its ability to escape from a local minimum and also by this that it generally gives good solutions compared to classical search algorithms. Secondly, we plan to apply our approach to real data from studies.

Acknowledgement

None.

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