DRIVER SCHEDULING OPTIMIZATION FOR PASSENGER TRANSPORT: INTEGRATING LEGAL CONSTRAINTS AND WORKLOAD FAIRNESS

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DOI: https://doi.org/10.57001/huih5804.2026.079

ABSTRACT

Road passenger transport in Vietnam has been developing rapidly, imposing increasing demands on safety, service quality, and resource utilization on transport companies. Consequently, driver scheduling becomes a complex problem, as it must simultaneously satisfy legal constraints on drivers' working hours and rest periods, continuous operational requirements, and the need to appropriately distribute driving hours among drivers. This study proposes a driver scheduling optimization model that incorporates these constraints. A genetic algorithm is employed with an appropriate encoding structure, and a mutation operator is designed to improve workload fairness of driving hours among drivers. Experimental results show that the proposed model generates feasible assignment schedules that comply with legal regulations and improve the workload fairness. Accordingly, the study provides decision support for transport companies in managing and allocating driver resources.

Keywords: *Road transportation, driver scheduling, hours-of-service regulations, genetic algorithm.*

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Received: 08/01/2026
Revised: 22/3/2026
Accepted: 30/3/2026

1. INTRODUCTION

The road transport industry plays a dominant role, meeting the majority of the population's increasing travel needs. In 2024, road passenger transport reached approximately 5.09 billion passengers, an 8.3% increase from 2023; notably, it accounted for up to 91.68% of the industry's total passenger volume [1]. Interprovincial passenger transport in Vietnam plays a strategic role in connecting regions and promoting socio-economic development. Within this context, the driver workforce plays a central role, acting as vehicle operators and as a decisive factor in safety, punctuality, and customer experience. Therefore, a critical issue is ensuring that driver scheduling is scientifically and efficiently planned to safeguard driver health and conserve resources for the enterprise. Specifically, Decree No. 168/2024/NĐ-CP [2] imposes strict legal constraints on drivers' driving and rest times. However, many transport enterprises still rely on manual and experience-based scheduling practices. As a result, driving hours are often unevenly distributed, legal driving limits may be violated, and vehicle and driver resources may not be efficiently utilized.

Driver and vehicle scheduling is a topic of interest to many researchers. Several representative works focus on developing optimization models combined with genetic algorithms to enhance schedule quality and minimize constraint violations [3, 4]. In addition to improving operational efficiency, many studies also emphasize the importance of complying with Hours of Service (HOS) regulations and of integrating legal requirements directly into scheduling and routing problems [5-7].

However, despite their significant contributions, prior studies on driver scheduling exhibit notable limitations when applied to Vietnamese road passenger transport. Most existing work focuses on urban bus systems or freight transport [3, 4], and those that integrate HOS regulations predominantly adopt European or North American legal frameworks [5-7], which differ substantially from Vietnamese regulations. Furthermore, most models optimize a single objective, typically minimizing the number of drivers or operational costs, while paying limited attention to driver workload fairness [9, 10]. In addition, the handling of overnight driving segments in daily driving-hour calculations remains insufficiently discussed in existing studies.

From these limitations, this study proposes an optimization model for driver scheduling to: (i) minimize the number of drivers required under limited resource conditions, (ii) comply with legal constraints in Vietnam, and (iii) ensure fairness in the distribution of driving hours among drivers. The research constructs a driver scheduling model at the weekly level and proposes a mutation operator variant designed to improve fairness in driving-hour assignments.

2. MODEL DEVELOPMENT

2.1. Problem Description

In this study, each round trip is divided into driving segments - the smallest units of work to be assigned to passenger bus drivers. A driving segment is defined by three components: the starting point, the ending point, and the driving duration. These driving segments are divided based on the locations of rest stops or transit hubs along a predetermined route - places where drivers can rest, change shifts, and attend to the personal needs of passengers.

Specifically, suppose an interprovincial route departs from bus station A to bus station B, with a stop at rest stop C; consequently, each leg (outbound or inbound) is divided into 2 driving segments, totaling 4 segments for the entire round trip (Figure 1). The problem becomes complex when the round-trip route is long, and dozens of such trips operate at different time slots, creating hundreds of segments that need driver scheduling over the course of a week. For long routes with many stops and a high operational frequency, the number of assignment combinations increases significantly, making it impossible to find an optimal solution solely based on experience.

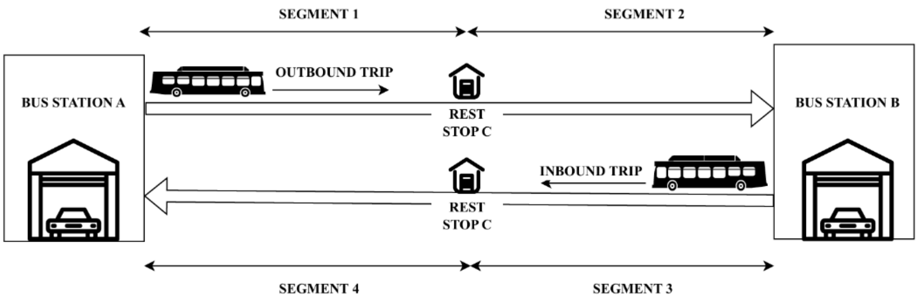


Figure 1. Diagram describing the division of driving segments

2.2. Driving Segment Modeling

According to Decree No. 168/2024/NĐ-CP, a driver's driving hour limit must be determined by the day, calculated from 00:00 to 24:00 of that specific day. This study proposes a time-axis representation method that enables the determination of the start and end times of each driving segment. This method enables the system to check for conflicts, calculate rest periods between trips and driving segments, and accurately compute driving hours for trips that extend overnight. For example, the weekly working time from 0:00 on Monday to 24:00 on Sunday is represented as a straight line divided into hourly intervals from 0 to 168, as illustrated in Figure 2, in which:

- t = 0 corresponds to 0:00 on Monday (the start date of the scheduling period).
- t = 168 corresponds to 24:00 on Sunday (the end date of the scheduling period).

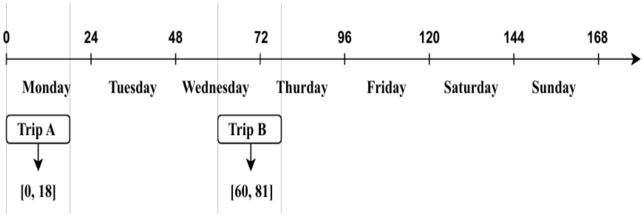


Figure 2. Time axis illustration

The total driving hours for each driver must be calculated according to the solar calendar day (the 0:00 - 24:00 timeframe of each day). Therefore, for driving segments that extend overnight, the driving duration must be allocated to each separate day. For example, if a driver begins a segment at 22:00 on Monday and finishes at 01:30 on Tuesday, the 3.5-hour segment is split as follows: 2 hours attributed to Monday (22:00 - 24:00) and 1.5 hours attributed to Tuesday (00:00 - 01:30). This ensures that the daily driving hour constraint is evaluated correctly against the solar calendar day (00:00 - 24:00), as required by Decree No. 168/2024/ND-CP.

2.3. Mathematical Model

Model Assumptions

- Velocity and driving time vary with traffic conditions and are estimated in advance based on historical operational data and planned schedules. This assumption is adopted to simplify the scheduling process under deterministic operating conditions, although actual travel times may vary in practice.

- Bus schedules are fixed, and departure, arrival, and rest-stop times are predetermined according to the company's operating plans.
- All trips are assumed to follow fixed round-trip operations.
- The number of operational vehicles is assumed to be sufficient, and vehicle breakdowns are not considered in the scheduling process.

Sets

D	Set of drivers
I	Set of driving segments per trip
K	Set of days in the scheduling period
T	Set of trips in the scheduling period

Parameter

$S_{t,k}$	Departure time of trip *t* on day *k*
$E_{t,k}$	Arrival time of trip *t* on day *k*
$s_{t,i,k}$	Start time of segment *i* on trip *t* on day *k*
$e_{t,i,k}$	End time of segment *i* on trip *t* on day *k*
dur_i	Duration of segment *i*
$max_{dailydrive}$	Limit of driving hours per day
$max_{weekdrive}$	Limit of driving hours per week
max_{driver}	Maximum number of drivers that can be mobilized
min_{rest}	Minimum rest time after completing a trip
ε	Allowable difference between the highest and lowest total driving hours among drivers
M	A very large constant (M>0)

Decision Variables

$X_{d,t,i,k}$	Binary variable; takes a value of 1 if driver d is assigned to driving segment i of trip t on day k, and 0 otherwise
Y_d	Binary variable; takes a value of 1 if driver d is utilized during the scheduling period, and 0 otherwise

Objective

Minimize the total number of drivers used in a scheduling period.

$$Min\ Z = \sum_{d=1}^{D} Y_d \quad (1)$$

Constraints

The constraints are constructed to ensure feasibility, legal compliance, and to reflect the reality of driver scheduling as follows:

$$\sum_{t=1}^{T}\sum_{i=1}^{I} X_{d,t,i,k} dur_i \le max_{dailydrive} \quad \forall \mathrm{d,k} \quad (2)$$

The total driving hours of driver d on any calendar day k must not exceed $max_{dailydrive}$. For segments that extend overnight, driving hours are split and allocated to each calendar day before evaluation, as described in Section 2.2.

$$\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{\mathrm{i}=1}^{\mathrm{I}} X_{d,t,i,k} dur_i \le \mathrm{max_{weekdrive}} \quad \forall \mathrm{d} \quad (3)$$

The total weekly driving hours of driver *d* does not exceed regulations. The total weekly hours are determined by the sum of the durations of all segments assigned to driver *d* within one week.

$$\sum_{d}^{D} X_{d,t,i,k} = 1, \forall i,t,k \quad (4)$$

All driving segments are assigned, and each is assigned to exactly one driver

$$X_{d,t,i,k} + X_{d,t',i',k} \le 1\ , \forall d,k \quad (5)$$
$$\forall (t,i),(t',i'): [s_{t,i,k}, e_{t,i,k}] \cap [s_{t',i',k}, e_{t',i',k}] \neq \emptyset$$

At any given time, a driver can drive a maximum of only one driving segment

$$X_{d,t,i,k} + X_{d,t',i',k} \le 1 \quad (6)$$
$$\forall d,k,t \neq t', i,i' \in I : \left[S_{t,k}, E_{t,k}\right] \cap \left[S_{t',k}, E_{t',k}\right] \neq \emptyset$$

At any given time, a driver can be assigned to only one trip.

$$X_{d,t,i,k} + X_{d,t',i',k} \le 1, \quad (7)$$
$$\forall d, \forall (t,k),(t',k): (S_{t',k} \le E_{t,k} + min_{rest})$$

After completing a trip, the driver must have a minimum rest period (min_{rest}) before starting the next trip. If the start time of the subsequent trip falls within the mandatory rest period (calculated from the end time of the previous trip), the driver cannot be assigned to it. For example: If Driver *d* finishes Trip 1 at 17:00 and the minimum rest is 2 hours, this driver cannot be assigned to any trip starting before 19:00.

$$\max_{d} \sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{\mathrm{i}=1}^{\mathrm{I}} X_{d,t,i,k} dur_i - \min_{d} \sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{\mathrm{i}=1}^{\mathrm{I}} X_{d,t,i,k} dur_i \le \varepsilon, \forall \mathrm{i,t,k} \quad (8)$$

This constraint limits the gap between the total driving hours of the driver who works the most and the driver who works the least, ensuring it does not exceed the threshold ϵ. This gap is chosen based on the company's human resource management policy

$$\sum_{d=1}^{D} Y_d \le max_{driver} \tag{9}$$

Ensures that the number of drivers scheduled does not exceed available resources.

$$\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{i=1}^{I} X_{d,t,i,k} \le Y_d M \ ,\forall d \tag{10}$$

This constraint establishes the relationship between the segment assignment decision variable and the driver usage indicator variable. If a driver is assigned any segment during the scheduling period (i.e., $X_{d,t,i,k} = 1$), then variable $Y_d = 1$ (driver d is used). M is a sufficiently large constant to ensure the constraint holds when $Y_d = 1$, but forces all $X_{d,t,i,k} = 0$ when $Y_d = 0$.

2.4. Genetic Algorithm (GA)

GA is an optimization algorithm based on the simulation of evolutionary mechanisms 0. GA was selected because the proposed driver scheduling problem is a large-scale combinatorial optimization problem with multiple complex constraints, making exact optimization approaches computationally expensive for practical applications. Compared with conventional exact methods, GA offers greater flexibility in handling scheduling problems and can obtain high-quality solutions within a reasonable computational time. In addition, GA has been widely applied in transportation scheduling studies due to its adaptability and robustness [3, 4].

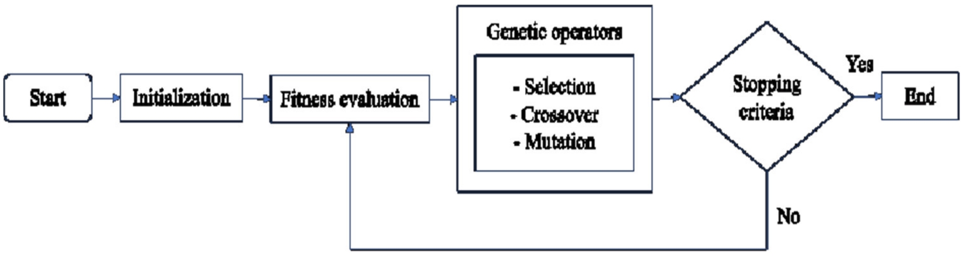


Figure 3. Flowchart of the Genetic Algorithm

GA simulates the evolution of individuals in a biological population over many generations to find the fittest individuals. In the driver scheduling problem, each individual in the population represents a scheduling plan. In each generation, scheduling plans of better quality (requiring fewer drivers and satisfying constraints) will have more opportunities to be selected, crossed over, and mutated, thereby generating new and better assignment schedules through each iteration. The GA procedure iterates through the steps illustrated in Figure 3 below: random initialization of a population of driver assignment schedules, fitness evaluation, selection of high-quality individuals, and application of crossover and mutation operators to generate a new generation. This process repeats across multiple generations until the stopping criterion is satisfied, at which point the best individual corresponds to a near-optimal driver assignment schedule.

2.4.1. Fitness Function

The quality of an individual is evaluated through a fitness function based on the following criteria:

- The number of drivers should be kept as low as possible.
- Constraint violations (overlapping driving times, exceeding daily/weekly driving limits, workload imbalance, etc.) are penalized with specific coefficients.

Specifically, the fitness function value is expressed as:

$$Fitness = P1 + a * P2 + b * P3 + c * P4 + d * P5 + e * P6 + g * P7 \tag{11}$$

In which:

Fitness: Fitness function value

P1: Total number of drivers used

P2: Total number of pairs of overlapping driving segments

P3: Total number of pairs of overlapping trips

P4: Total hours exceeding the daily driving limit across all drivers and all days

P5: Total hours exceeding the weekly driving limit across all drivers

P6: The workload fairness exceeds the threshold ϵ between the drivers with the least and most driving hours

P7: Excess amount over the available driver resources

a, b, c, d, e, g: Penalty coefficients

The penalty coefficients reflect constraint priority: hard constraints (overlapping assignments, driver limit exceedance) receive the highest weights, followed by legal driving hour limits, with workload fairness assigned the lowest weight as a soft constraint. Values were determined empirically to ensure the GA prioritizes feasibility before optimizing fairness.

Based on fitness, good schedules (low fitness) are prioritized for selection and crossover to pass on good traits to the next generation, while poor-quality schedules are gradually eliminated. This process repeats over many generations, allowing the population to evolve; accordingly, the schedule gradually converges toward an optimal assignment that satisfies constraints and minimizes the number of drivers used without violating constraints.

2.4.2. Chromosome Structure

Each chromosome represents a scheduling plan for all trips in the scheduling period, Chromosome = [S1, S2, S3, ..., Sn], where *n* is the total number of segments to be assigned in one period.

Gene: Each gene *Sn* corresponds to a specific driving segment. The position of the gene in the chromosome is mapped to a set of indices (*k*, *t*, *i*), where *k* is the day of the week, *t* is the trip of the day, and *i* is the driving segment of that trip.

Allele: Represents the value of a gene, corresponding to the ID code of the driver assigned to that segment.

For example, to schedule for 2 days, each with 1 trip consisting of 3 segments (6 segments total), a chromosome might be encoded as shown in Figure 4.

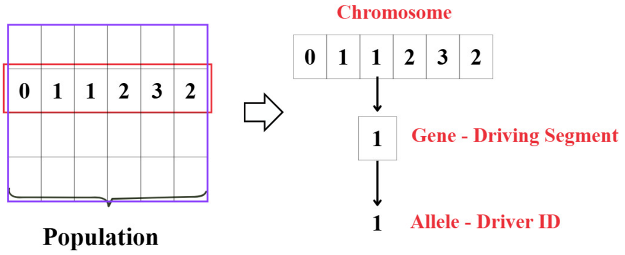


Figure 4. Example of a typical chromosome

When decoding the chromosome in Figure 4, a complete driver scheduling plan is obtained as shown in Table 1.

Table 1. Decoding of a typical chromosome

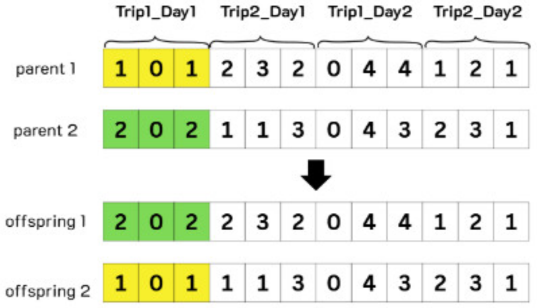
Gene Position	Day	Trip	Driving Segment	Driver ID (Allele)
1	1	1	1	**0**
2	1	1	2	**1**
3	1	1	3	**1**
4	2	1	1	**2**
5	2	1	2	**3**
6	2	1	3	**2**

2.4.3. Selection Operator

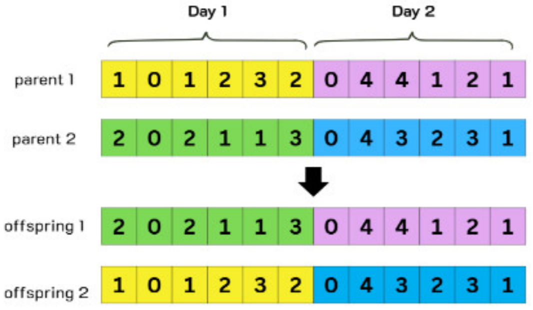
In this study, the selection process uses the n-size tournament selection method. At each selection round, a group of *n* individuals is randomly chosen from the population to "compete" by comparing their fitness values. The individual with the best fitness value is selected for the crossover set. This process is repeated until the required number of individuals is collected.

2.4.4. Crossover Operator

The chromosome is divided into blocks, where each block corresponds to all segments of a single trip (trip block) or all segments in a single day (day block). When crossover occurs, the algorithm randomly selects one or more blocks and swaps them in their entirety between two chromosomes, leaving the remaining parts unchanged, creating two corresponding offspring. This study utilizes two types of crossover: swapping trip blocks and swapping day blocks between two schedules.



a) Swapping Trip blocks



b) Swapping Day blocks

Figure 5. Crossover examples

2.4.5. Mutation Operator

The mutation operator maintains genetic diversity in the population. This study proposes a mechanism called "workload fairness-improving mutation operator". Unlike traditional operators that only introduce random changes, this operator actively detects pairs of drivers where one is overloaded, then transfers a driving segment from the overloaded driver to an idle driver to distribute driving hours more fairly and accelerate convergence. The operating principle is illustrated in Figure 6.

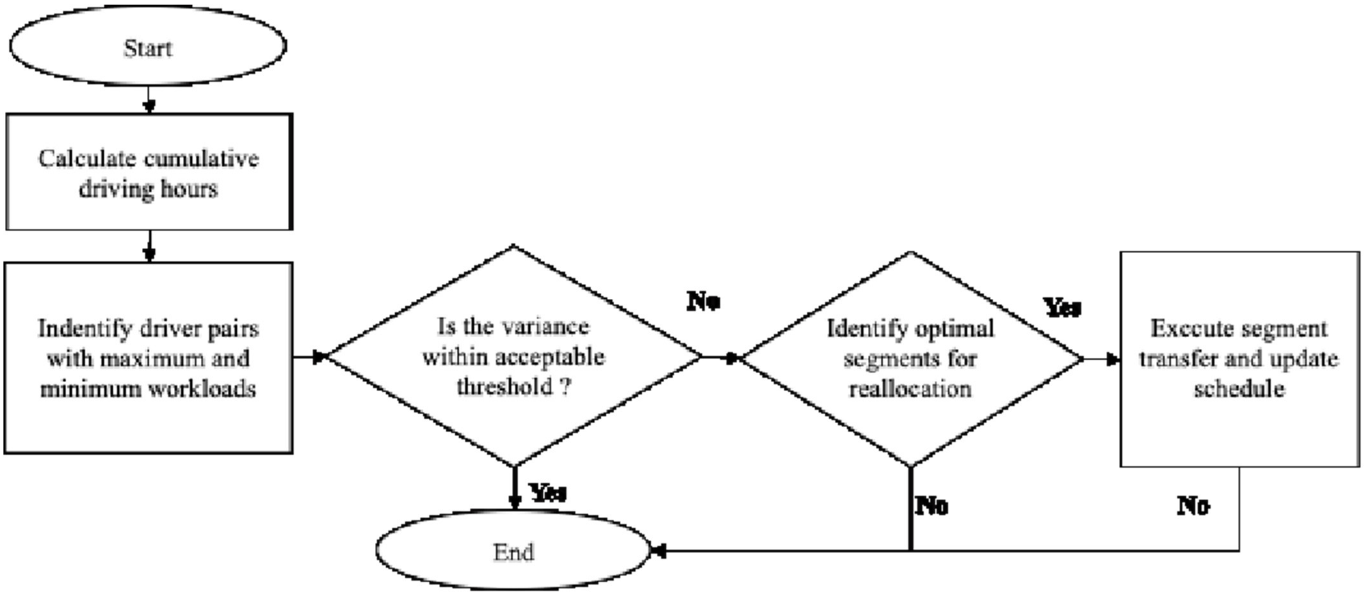


Figure 6. Schematic illustration of the workload fairness-improving mutation operator principle

The operator identifies the overloaded driver (highest total driving hours) and the underutilized driver (lowest total driving hours); it is activated only when their gap exceeds the threshold ε\varepsilon ε. Among all segments assigned to the overloaded driver, the operator selects the longest one for transfer, prioritizing maximum imbalance reduction in a single intervention. The transfer is accepted only if it introduces no new violations - no schedule conflicts, no exceedance of the daily (10 hours/day) or weekly (48 hours/week) driving limits. The effectiveness of this operator is validated in Section 3.6.

3. EXPERIMENTAL RESULTS AND ANALYSIS

3.1. Description of the Typical Case Study

The typical case study is based on the "Can Tho - Da Lat" interprovincial passenger route operated by a passenger transport company. This is a long-distance route with a total distance of approximately 820 km and an average round-trip travel time of 16 hours (excluding rest time at stops). On this route, the bus stops at 2 rest stops, dividing each leg into 3 stages, each corresponding to a different driving segment with a different duration; thus, there are a total of 6 driving segments per round trip that need to be assigned, as illustrated in Figure 7.

Each day, the company operates 12 trips on this route, with departure and arrival schedules evenly distributed over 24 hours (Table 2). With a scheduling period lasting one week, the problem is as follows: 84 trips, 504 driving segments to be assigned, and 34 drivers.

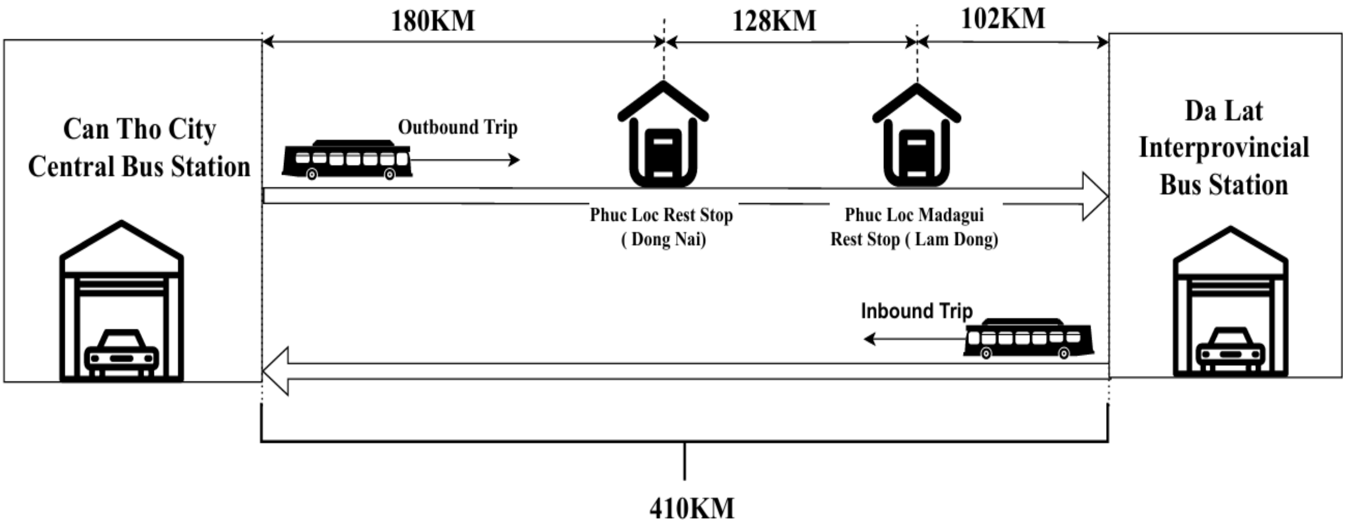


Figure 7. Illustration of moving segments on the Can Tho - Da Lat route

Table 2. Information on departure and arrival schedules of daily trips

Trip	Departure Time	Arrival Time	Trip	Departure Time	Arrival Time
1	0:00	16:00	7	12:00	4:00
2	2:00	18:00	8	14:00	6:00
3	4:00	20:00	9	16:00	8:00
4	6:00	22:00	10	18:00	10:00
5	8:00	0:00	11	20:00	12:00
6	10:00	2:00	12	22:00	14:00

Table 3. Information on segments of the Can Tho - Da Lat route

Driving Segment	Starting Point	Destination	Distance (km)	Duration (hours)	Trip
1	Can Tho City Central Bus Station	Phuc Loc Rest Stop (Dong Nai)	180	3.5	Outbound
2	Phuc Loc Rest Stop (Dong Nai)	Phuc Loc Madagui Rest Stop (Lam Dong)	128	2.5	Outbound
3	Phuc Loc Madagui Rest Stop (Lam Dong)	Da Lat Interprovincial Bus Station	102	2	Outbound
4	Da Lat Interprovincial Bus Station	Phuc Loc Madagui Rest Stop (Lam Dong)	102	2	Inbound
5	Phuc Loc Madagui Rest Stop (Lam Dong)	Phuc Loc Rest Stop (Dong Nai)	128	2.5	Inbound
6	Phuc Loc Rest Stop (Dong Nai)	Can Tho City Central Bus Station	180	3.5	Inbound
Total			**820**	**16**	**Full Trip**

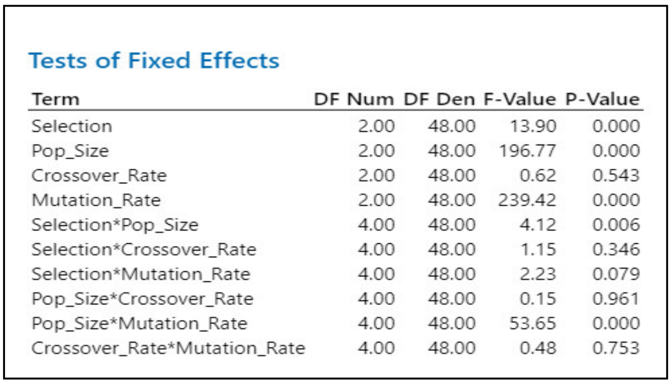
3.2. Parameter Adjustment for GA

Table 4. Observed parameters and corresponding levels

Parameter	Level 1	Level 2	Level 3
Population Size	100	200	300
Crossover Rate	0.70	0.80	0.90
Mutation Rate	0.05	0.10	0.15
Selection Size	3	4	5

The study conducted experiments with various GA parameter sets on the same input dataset to identify the optimal parameter combination for the optimized model. The parameters and adjustment levels were based on previous research [9-12] and are shown in Table 4. From this, 81 value combinations were surveyed using the full factorial design method. Each combination was repeated 50 times with a maximum of 1000 generations. The mathematical model and algorithm were programmed in Spyder 6, and experiments were performed on a computer with an Intel(R) Core(TM) i7-6600U CPU @ 2.80 GHz, and 8GB RAM.

The ANOVA analysis results showed that the mutation rate and population size had the most significant influence on the fitness function value (Figure 8a). The main effect and interaction charts (Figure 8b-c) show that as population size and mutation probability increase, fitness decreases significantly. Based on these observations, the proposed GA parameter set is: Pop_Size = 300, Selection = 4, Crossover_Rate = 0.70, and Mutation_Rate = 0.15.



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Tests of Fixed Effects

Term                          DF Num  DF Den  F-Value  P-Value
Selection                       2.00   48.00    13.90    0.000
Pop_Size                        2.00   48.00   196.77    0.000
Crossover_Rate                  2.00   48.00     0.62    0.543
Mutation_Rate                   2.00   48.00   239.42    0.000
Selection*Pop_Size              4.00   48.00     4.12    0.006
Selection*Crossover_Rate        4.00   48.00     1.15    0.346
Selection*Mutation_Rate         4.00   48.00     2.23    0.079
Pop_Size*Crossover_Rate         4.00   48.00     0.15    0.961
Pop_Size*Mutation_Rate          4.00   48.00    53.65    0.000
Crossover_Rate*Mutation_Rate    4.00   48.00     0.48    0.753
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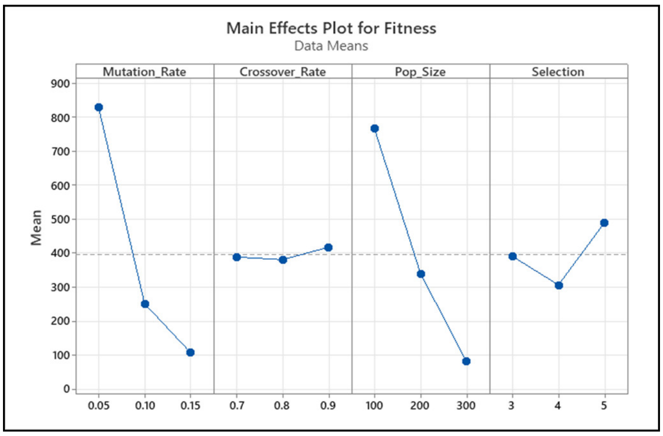
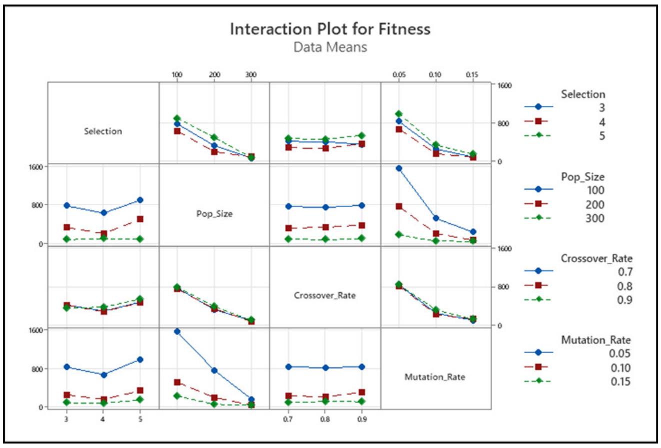
a) ANOVA analysis results on Minitab



b) Main effects plot for fitness



c) Interaction plot for parameters affecting fitness

Figure 8. Experimental analysis results

3.3. Scheduling Results

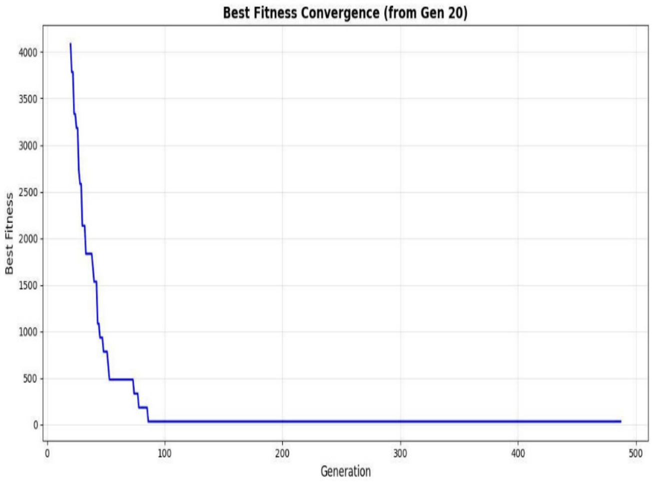


Figure 9. Fitness evolution chart after optimization

The selected GA parameter combination was used to solve the proposed optimization model. The convergence chart in Figure 9 shows that the fitness function value decreases gradually and converges stably after approximately 100 generations, indicating the GA's search efficiency and convergence capability for the driver scheduling problem. The scheduling results presented in Table 5 show that the model generates a feasible assignment schedule with no constraint violations, while ensuring a relatively even distribution of driving hours.

Table 5. Experimental results

Evaluation Criteria	Unit	Results
Total number of driving segments to be assigned in the scheduling period	Segment	504
Number of drivers used	Driver	34
Number of violated constraints	Times	0
Driver utilization rate (Total actual driving hours/Total theoretical available driving hours)	%	82.35
Highest total driving hours of a driver	Hour	43
Lowest total driving hours of a driver	Hour	35
Workload fairness gap in driving hour distribution (max-min)	Hour	8
Standard deviation of total driving hours among drivers	Hour	2.22
Average number of driving segments per driver	Segment	15
Average number of trips assigned per driver	Trip	8

3.4. Model evaluation

For model evaluation, the proposed approach was compared with three scheduling methods. The first method is sequential assignment (SA), in which driving segments are assigned to drivers in the existing assignment order, reflecting conventional manual scheduling practices. The second method is round robin (RR), which distributes driving segments cyclically among drivers to achieve a relatively balanced workload allocation. The third method is greedy search (GS), in which each driving segment is assigned to the first feasible driver that satisfies the current daily and weekly driving-hour constraints. These methods were selected to represent common practical and heuristic scheduling strategies for comparative analysis.

Table 6 shows that the proposed model outperformed the compared scheduling methods. Significant differences arise in constraint compliance and workload fairness. SA and GS produce a substantial number of violated constraints because they mainly rely on sequential or local assignment decisions without comprehensively considering the overall scheduling structure and workload balance, rendering their resulting schedules legally infeasible for practical deployment. RR achieves zero violations but relies on a rigid cyclic structure that offers limited optimization flexibility. In contrast, the proposed model integrates multiple operational and legal constraints within a unified mathematical optimization framework and applies the global search capability of GA to explore higher-quality scheduling solutions. As a result, the proposed model is the only method that simultaneously achieves zero violated constraints and the most equitable driving-hour distribution, as reflected by the lowest workload fairness gap and standard deviation among all methods. Additionally, the highest total driving hours assigned to any driver under the proposed model remain below the legal limit, directly supporting driver safety, reducing fatigue risk, and potentially providing operational cost savings through improved resource utilization and reduced legal violations.

Table 6. Experimental results across scheduling methods

Evaluation Criteria	**Unit**	**SA**	**RR**	**GS**	**Proposed model**
Total number of driving segments to be assigned in the scheduling period	Segment	504	504	504	504
Number of drivers used	Driver	34	34	34	34
Number of violated constraints	Times	24	0	40	0
Driver utilization rate	%	82.35	82.35	82.35	82.35
Highest total driving hours of a driver	Hour	48	48	48	43
Lowest total driving hours of a driver	Hour	14	36.5	18.5	35
Workload fairness gap in driving hour distribution (max-min)	Hour	34	11.5	29.5	8
Standard deviation of total driving hours among drivers	Hour	13.45	3.76	13.43	2.22
Average number of driving segments per driver	Segment	14	15	14	15
Average number of trips assigned per driver	Trip	12	15	6	8
Executing time of the methods	Seconds	10	15	15	300

3.5. Sensitivity Analysis Based on Changes in Total Drivers Used

In this study, resource change scenarios included: reducing by 20%, reducing by 10%, keeping the current level (34 drivers), increasing by 10%, and increasing by 20% to investigate the influence of the number of drivers used on the scheduling model results. Analysis shows that the number of available drivers affects the outcome (Table 7). When the driver pool is below the required level (under 34 drivers), the feasible solution space narrows, leading to legal violations and overlapping assignments. Furthermore, the system must make full use of available staff, which can pose safety risks due to potential driver fatigue. Conversely, increasing the number of drivers beyond 34 does not improve operational efficiency but only reduces the driver mobilization rate and incurs unnecessary costs.

Table 7. Comparison of five scenarios regarding the number of drivers

Criteria	**Unit**	**-20%**	**-10%**	**Current Level**	**10%**	**20%**
Number of drivers	People	27	30	**34**	37	41
Number of drivers used	People	27	30	**34**	34	34
Driver utilization rate	%	100	93.33	**82.35**	75.68	62.29
Standard deviation of driving hours	Hours	1.99	2.43	**2.22**	2.33	2.64
Trip/segment overlaps	Times	118	17	**0**	0	0
Driving hour/day violations	Hour	1.5	0	**0**	0	0
Driving hour/ week violations	Hour	48.5	0	**0**	0	0

3.6. Evaluating the Effectiveness of Workload Fairness-Improving Mutation Operator in Driving Hour Distribution

This operator was proposed to improve the fairness of driving hour workloads among drivers. To evaluate its contribution, the study compared GA performance in two cases: (1) using the Workload fairness-improving mutation operator and (2) not using it. GA parameters remained the same in both cases, with 30 repetitions per case. Table 8 presents the statistical comparison. The results show that applying the fairness-improving mutation (Case 1) brought significant improvements. Compared to Case 2, the results were better in three aspects: (1) more stable fitness values, (2) faster convergence speed, and (3) fairer distribution of driving hours.

Table 8. Statistical comparison of evaluation criteria

Indicator	Case	Min	Max	Mean	Median	Std.
Objective function value *(Optimal number of drivers)*	**Case 1**	**33.00**	**35.00**	**33.75**	**34.00**	**0.62**
	Case 2	33.00	35.00	34.00	34.00	0.70
Fitness value	**Case 1**	**33.00**	**35.00**	**33.75**	**34.00**	**0.62**
	Case 2	33.00	2735.00	979.00	934.00	628.03
Number of generations to converge	**Case 1**	**473.00**	**772.00**	**576.75**	**568.50**	**71.64**
	Case 2	849.00	1,000.00	985.00	1,000.00	38.48
Driving hour gap	**Case 1**	**7.50**	**8.00**	**7.95**	**8.00**	**0.15**
	Case 2	8.00	17.00	11.15	11.00	2.09

4. CONCLUSIONS

This study proposes an optimization model for the driver scheduling problem in passenger transport that simultaneously integrates legal constraints on driving and rest hours, operational feasibility requirements, and fairness criteria for distributing driving hours among drivers. The problem is solved using a GA with a mutation operator designed to improve workload fairness, enabling the creation of feasible assignment schedules that comply with regulations while improving workload fairness among drivers.

With its flexible structure, this research model has the potential to expand and be applied to transportation cases with similar characteristics, such as urban buses, long-distance coaches, or freight transport. At the same time, the model allows for adjustments to accommodate future changes in legal regulations or corporate policies. From a management perspective, the research results indicate that applying scheduling tools based on optimization models can effectively replace manual assignment methods, contributing to legal compliance, improved resource utilization efficiency, and a move toward sustainable human resource management.

However, the study still has several limitations, including the assumption that travel time is deterministic, which fails to account for factors such as traffic congestion, vehicle breakdowns, or sudden driver absences. Furthermore, the research has only been verified on a single typical route and has not yet considered multi-route scenarios. In future studies, the model could be expanded by integrating uncertainty and real-time rescheduling mechanisms, applied to multi-route networks, and developed into multi-objective models to simultaneously balance operational efficiency, service quality, and driver welfare across various regulatory contexts.

APPENDIX

Model parameters, penalty coefficients

Parameter	Description	Value	Unit	Explanations
$max_{dailydrive}$	Maximum daily driving hours per driver	10	Hour	Decree No. 168/2024/NĐ-CP
$max_{weekdrive}$	Maximum weekly driving hours per driver	48	Hour	Decree No. 168/2024/NĐ-CP
min_{rest}	Minimum rest time between consecutive trips	0.5	Hour	Estimated from actual turnaround operations on the Can Tho - Da Lat route
max_{driver}	Maximum number of available driver	34	Driver	Available driver workforce of the transport company
ε	Maximum allowable workload fairness gap between Min and Max untilized driver	8	Hour	Estimated based on acceptable workload distribution observed on the Can Tho–Da Lat route
M	Big-M constant	10,000	-	A sufficiently large constant
a	Penalty - overlapping driving segments	1,000	-	Highest priority, renders schedule operationally infeaible
b	Penalty - overlapping trips	1,000	-	Highest priority, renders schedule operationally infeaible
c	Penalty - daily driving hours violations	500	-	Legal compllance requirement per Decree No.168/2024/NĐ-CP

d	Penalty - weekly driving hour violations	500	-	Legal compllance requirement per Decree No.168/2024/NĐ-CP
e	Penalty - workload fairness gap exceeding	300	-	Operational perference lower weight allows GA to prioritize feasibility first
g	Penalty - exceeding available driver limit	2,000	-	Strictest penaly, violating resource limit makes the schedule undeployable

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