Optimizing Customized Bus Routing and Maximum Seat Occupancy Rate Under the Influence of Epidemic Outbreaks

Keywords: Customized bus, vehicle routing problem, seat occupancy rate optimization, epidemic, Wells–Riley model

1 INTRODUCTION

The COVID-19 pandemic drastically reduced public transportation usage, prompting Chinese cities to promote customized bus (CB) services as a safer alternative. While CB services offer flexible, efficient transit with reduced infection risk, operators must balance safety measures with profitability, providing valuable lessons for future epidemic preparedness.

CB route design is the primary decision variable in the paper, as it directly influences in-vehicle travel time and infection risk. CB routing problem has been formulated as vehicle routing problem with pickup and delivery (VRPPD). However, existing CB-VRP models have several limitations:

Firstly, most models assume fixed travel demand, neglecting the impact of travel cost changes on demand. Secondly, the in-vehicle infection risk cost during epidemics is not considered (e.g., Ma, Zeng, and An 2023), despite its significant influence on passenger travel behavior. Thirdly, as stated in (Huang et al. 2023), in a CB scenario, the social distance in a vehicle is associated with the seat occupancy rate, while the duration of ride is influenced by route design. However, CB route design model that optimizes the seat occupancy rate setting has not yet been reported. In addition, existing models do not consider the social responsibility of operators in preventing and controlling epidemics. Finally, current algorithms lack efficient solutions for integrated route planning and seat occupancy rate optimization (e.g., Ma, Yang, and Li 2023).

The main contributions of this paper are as follows:

1. This paper integrates the maximum seat occupancy rate setting problem into the CB route planning model under the assumption of elastic demand.
2. Considering the in-vehicle infection risk cost in terms of the passenger travel cost, a modified Wells–Riley model is used to estimate the in-vehicle infection risk cost.
3. The genetic algorithm combined with a simulated annealing algorithm and embedded local search descent algorithm (M-SAGA) is adopted.

2 MODEL FORMULATION

2.1 In-vehicle infection risk cost

To assess the in-vehicle infection risk cost of CB, the Wells–Riley model (Riley, Murphy, and Riley 1978) is modified to directly correlate the risk with the number of passengers and the duration of the ride. The infection probability on section (i, j) of route r can be calculated as:

$$P_{i,j}^{r} = 1 - \exp\left((f_{i,j}^{r} \cdot \alpha \cdot \zeta \cdot t_{i,j} \cdot \lambda) / (\varepsilon \cdot \sqrt{\frac{\theta}{f_{i,j}^{r}}}) \right), \forall i, j \in N^{+}, r \in R, \tag{1}$$

where $f_{i,j}^{r}$ is the number of passengers per vehicle for section (i, j) of route r, $t_{i,j}$ is the in-vehicle exposure time for section (i, j), ζ is a coefficient determined by the quanta production rate and respiratory ventilation rate, and λ is the mask filtration coefficient.

The in-vehicle infection probability of passengers from OD pair g can be calculated as:

$$P^{g} = 1 - \prod_{i,j \in N^{+}, r \in R} (1 - x_{i,j}^{r,g} \cdot P_{i,j}^{r}), \forall g \in G, \tag{2}$$

where $1 - x_{i,j}^{r,g} \cdot P_{i,j}^{r}$ is the probability of not infecting passengers from OD pair g for section (i, j) of route r. Finally, the in-vehicle infection risk cost of OD pair C_{inf}^{g} can be determined by P^{g}, the number of days required to recover from infection r_{day}, and the loss per day rest C_{day}, which is formulated as:

$$C_{\text{inf}}^{g} = P^{g} \cdot r_{\text{day}} \cdot C_{\text{day}}, \forall g \in G. \tag{3}$$

2.2 Optimization model

In this paper, the objective is to maximize the operator's profit while considering the operator's responsibility for epidemic prevention during outbreaks. The CB routing and maximum seat occupancy rate setting optimization model can be formulated as follows:

$$\max Z(\mathbf{x},\mathbf{y},\boldsymbol{\delta},\mathbf{k}) = \sum_{g\in G}\left(d^g C_{\text{fare}}^g\right) - \eta_1 \sum_{r\in R} k^r - \eta_2 q_{\text{veh}} \sum_{r\in R}\sum_{i,j\in N}\left(y_{i,j}^r t_{i,j} k^r\right) - \eta_3 \sum_{g\in G}\left(P^g d^g\right), \quad (4)$$

subject to

$$y_{i,j}^r = \begin{cases} 1, \sum_{g\in G} x_{i,j}^{r,g} > 0 \\ 0, \text{otherwise} \end{cases}, \forall i,j \in N, r\in R, \quad (5)$$

$$\sum_{i\in N, i\neq n} x_{i,n}^{r,g} = \sum_{j\in N, j\neq n} x_{n,j}^{r,g}, \forall n \in N^+, r\in R, g\in G, \quad (6)$$

$$\delta_{\min} \leq \delta^r \leq \delta_{\max}, \forall r \in R, \quad (7)$$

$$x_{i,j}^{r,g} \in \{0,1\}, \forall i,j \in N, g\in G, r\in R, \quad (8)$$

and additional constraints include flow conservation constraints, each vehicle starts and ends at the depot and route length limitations. $y_{i,j}^r$ and $x_{i,j}^{r,g}$ is binary decision variables indicating whether section (i,j) is travelled by route r (and serving OD pair g), δ^r is a positive continuous decision variable indicating the maximum seat occupancy rate along route r, and k^r is a positive integer indicating the number of vehicles dispatched on route r, which is required to satisfy all travel demands for this route. The number of vehicles dispatched on route r is formulated as:

$$k^r \geq \sum_{g\in G}\left(x_{i,j}^{r,g} \cdot d^g\right)/(\tau \cdot \delta^r), \forall i,j \in N^+, r\in R, \text{ and} \quad (9)$$

$$k^r \in \{1,2,3,\ldots\}, \forall r \in R. \quad (10)$$

d^g is travel demand and C_{fare}^g is fare cost of OD pair g. η_1, η_2, η_3 are unit costs of fixed operating cost, running cost and penalty, respectively. τ is seat number of a vehicle. Constraint (5) requires passengers to travel on valid routes and vehicles not travel empty except for entering or existing the depot; constraint (6) requires passengers with the same OD pair to travel on the same route. Constraints (7) - (10) define the variable domains.

3 SOLUTION ALGORITHM

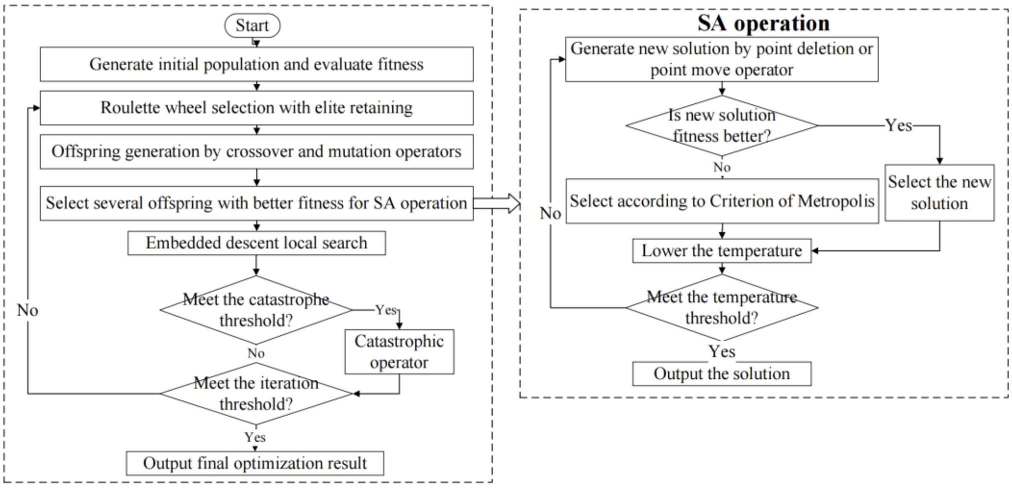

Figure 1 –*Basic flow diagram of M-SAGA*

To enhance the computational efficiency, a hybrid algorithm called M-SAGA based on genetic algorithm (GA) combined with simulated annealing (SA) and an embedded descent local search algorithm is proposed to optimize the route planning and the maximum seat occupancy rate setting problems. The overall framework of the M-SAGA algorithm is based on the GA procedure, with the SA procedure applied in the neighborhood search phase to improve the quality of the solution (Sun et al. 2020). A local search algorithm for determining the maximum seat occupancy rate is also developed to enhance computational efficiency. The basic flow diagram of the M-SAGA algorithm is shown in Figure 1.

4 NUMERICAL EXAMPLES

4.1 Significance of maximum seat occupancy rate optimization

An example network with one origin and destination node was developed to illustrate the significance of optimizing the maximum seat occupancy rate. As shown in Figure 2, the objective value first increases and then decreases as the maximum seat occupancy rate increases. This is because, as the maximum seat occupancy rate initially increases, the number of required vehicles decreases significantly, increasing the objective value. However, further increases elevate infection risk, reducing passenger willingness to choose CB and ultimately lowering the objective value.

It can be concluded from the result that properly setting the maximum seat occupancy rate can give significantly better result (i.e., profit under infection risk control) during epidemic outbreaks.

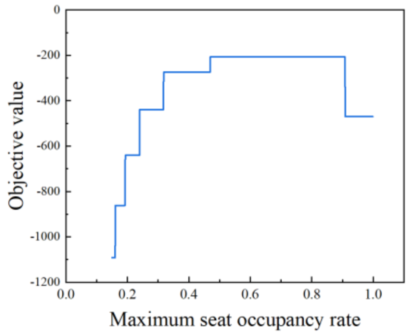

Figure 2 –*Objective value against maximum seat occupancy rate*

4.2 Significance of considering the in-vehicle infection risk cost

This example compared two scenarios using the Sioux-Falls network: without (Scenario A) and with (Scenario B) consideration of in-vehicle infection risk cost on passengers' travel behavior during epidemic outbreaks. Key measures are evaluated using both scenarios are presented in Table 1.

Table 1 –*Comparison of the Key Measures in Scenarios A and B*

Scenario	System infection rate	Average route length	Optimal maximum seat occupancy rate	Fleet size	Number of passengers	Profit
A	0.0362	97.4	0.995	63	3091	136,740.2
B	0.0335	88	0.971	59	2821	115,340.7
Percentage difference	**8.2%**	**10.7%**	2.4%	**6.8%**	**9.6%**	**18.6%**

As shown in Table 1, the system infection rate of Scenario B is 8.2% lower than Scenario A, indicating that the system infection rate will be significantly reduced if passengers are able to perceive the in-vehicle infection risk correctly during epidemic outbreaks.

For service planning, Scenario B shows lower average route length, optimal maximum seat occupancy rate, and fleet size compared to Scenario A. This is because operators aim to mitigate infection risk and attract passengers by limiting route length and seat occupancy rate, which are negatively correlated with infection risk. Additionally, number of passengers and profit obtained in Scenario B are also much lower than Scenario A. When passengers are aware of the infection risk, they will be less willing to travel, resulting in a significant drop in CB revenue and profit.

These results imply that neglecting passengers' perceptions on in-vehicle infection risk will lead to overestimation of CB passenger demand, CB fleet size required, and most importantly CB profit, which may threaten the survival of CB companies during epidemic outbreaks.

4.3 Performance of the M-SAGA

To illustrate the efficiency of the proposed solution method, the effectiveness of the SA operation, and the embedded descent local search algorithm in the M-SAGA algorithm, this example compared the performance of three algorithms: GA with embedded descent local search, SAGA without embedded descent local search, and M-SAGA (which combines both). A 30-nodes network is used to compare the GA, SAGA and M-SAGA performances. Table 2 shows a summary of the average computational results of 10 runs obtained by the three algorithms.

As shown in Table 2, the improvement between the objective values obtained by the GA and M-SAGA is significant, demonstrating that the SA operation can effectively prevent premature convergence to a local optimum. Also, comparing the SAGA and M-SAGA, the improvement between the objective values is significant, suggesting that the embedded local search can significantly enhance solution quality (i.e., higher fitness value of optimal solution) although it may require longer computational time.

Table 2 –*Performance Comparisons*

Number of nodes	GA		SAGA		M-SAGA		Difference between GA and M-SAGA		Difference between SAGA and M-SAGA	
	Avg. time (s)	Avg.obj	Avg. time (s)	Avg.obj	Avg. time (s)	Avg.obj	Time (%)	Obj (%)	Time (%)	Obj (%)
30	5,772.7	39,491.6	6,694.3	47,252.3	7,318.3	50,106.5	21.12	**21.18**	8.53	**5.70**

5 CONCLUSION

This paper proposed a model that jointly optimizes routing and maximum seat occupancy rate setting of customized bus (CB), incorporating the in-vehicle infection risk cost into the passengers' travel cost under the assumption of elastic demand during an epidemic outbreak. A modified Wells–Riley model was adopted to estimate the in-vehicle infection risk affected by routing and seat occupancy rate decisions. Linearization techniques were applied to simplify the proposed model. A hybrid algorithm based on Genetic Algorithm (GA) combined with Simulated Annealing (SA) operation and an embedded descent local search algorithm was developed to solve this problem.

Numerical studies were conducted to illustrate the model properties and the effectiveness of the proposed solution method. Results indicate that jointly optimizing routing and maximum seat occupancy rate of CB can significantly improve the profitability of CB while controlling total infection risk of passengers during epidemic outbreaks. Passengers' perception on in-vehicle infection risk is helpful in reducing system infection risk. Neglecting this perception may prevent CB operators from achieving optimal operational efficiency and profitability due to overestimate of passenger demand, which may threaten the survival of CB companies during epidemic outbreaks. Moreover, the integration of both the embedded local search heuristic and SA operations proposed in this paper can significantly improve solution quality especially for larger-scale networks compared with GA.

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