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SYNCHRONIZING PUBLIC TRANSPORT SCHEDULES WITH GENETIC ALGORITHMS: CHOOSING THE HEURISTIC PARAMETERS

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Resume

Synchronized timetables are crucial for public transportation, yet optimizing them remains complex. While Genetic Algorithms (GAs) address this challenge effectively, their success depends on parameter tuning. In this study was examined how the GA parameters affect schedule synchronization, using a stochastic simulation model to evaluate the fitness of alternative solutions. It is found that the larger population sizes improve solution quality, and higher crossover probabilities enhance overall performance. Conversely, increasing mutation rates or the number of attempted mutations reduces the algorithm's ability to converge on optimal timetables. Those findings provide researchers and practitioners with data-driven insights for efficiently deploying GAs in public transit optimization.

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1 Introduction

One key determinant of public transportation efficiency is schedule synchronization. Synchronized timetables minimize passenger waiting times, reduce transfer costs, and enhance the overall attractiveness of public transit. Achieving optimal synchronization is a complex combinatorial optimization problem, often characterized by a vast search space and multiple, conflicting objectives. Consequently, researchers have employed a variety of heuristic and metaheuristic approaches, such as Simulated Annealing (SA), Tabu Search, and Ant Colony Optimization (ACO), to find the high-quality solutions within reasonable computational limits [1]. Genetic algorithms (GAs) are widely used to tackle scheduling challenges because of their robustness and ability to explore a diverse solution space.

While the GAs have shown considerable potential

for public transport synchronization, their performance depends critically on selecting the right heuristic parameters. Parameters such as population size, crossover rate, mutation rate, and selection mechanisms significantly influence the algorithm's convergence speed and solution quality. Suboptimal parameter choices can lead to premature convergence, an inability to find near-optimal solutions, or excessively long computation times, thereby diminishing the practical utility of the GA-based approach to synchronizing schedules within the public transport system.

In this paper is addressed the crucial role of heuristic parameter selection in synchronizing public transport schedules using GAs. Within this research was investigated how different parameters affect the effectiveness of GAs in this domain. By analyzing how parameter settings affect optimization performance, this study aim was to provide insights for researchers and practitioners seeking to deploy GAs to solve the

synchronization problem within a public transport network. Ultimately, this study's objective is to enhance the performance of GA-based solutions, thereby supporting the development of more efficient public transportation systems.

As a tool to evaluate the efficiency of the public transport system, the simulation model was first proposed and described in the paper [2]. The authors applied this tool while solving the synchronization problem for the public transport network in Verkhniodniprovs'k, Ukraine [3]. The simulation model generates random trip demand within the public transport system, mimics the servicing process, and returns the estimated total waiting time for passengers.

This paper is organized as follows. In Section 2, the literature on applying the GA to public transport timetable synchronization is reviewed. The proposed approach, which combines GA with system simulations, is described in Section 3. The methodology for investigating the impact of GA parameters on the results is outlined in Section 4. The findings from the experimental studies are presented in Section 5, and a summary and recommendations for future research are provided in Section 6.

2 Literature review

Previously, research on timetable synchronization was focused on optimizing a single objective, such as minimizing passenger waiting time or total costs, including operational costs. Yet a significant shift is occurring, with more recent studies adopting a multi-criteria approach. This broader perspective allows researchers to address the problem's full complexity by considering objectives such as minimizing passenger time (waiting and travel), reducing schedule deviations, minimizing vehicle requirements, and maximizing transfer opportunities. This evolution reflects a deeper understanding of the interrelated factors crucial to effective timetable synchronization [1].

The GAs have been widely applied to the complex problem of public transport schedule synchronization, addressing a broad range of optimization objectives. A primary focus in many studies has been minimizing passenger inconvenience. For instance, Chakroborty et al. used GAs to minimize the combined transfer and initial waiting times [4]. Similarly, Wu et al. sought to reduce total passenger waiting times in the Beijing metro network, with an added emphasis on equitable waiting times across stations [5], while Tuzun and Yilmaz formulated an objective to minimize both passenger waiting times and missed transfers [6]. Building on this passenger-centric approach, Niu et al. addressed passenger waiting time while innovatively incorporating an in-train crowding factor to enhance comfort and maximize operator profits [7]. The challenge of the last-train synchronization, crucial for extending network

accessibility, has also been tackled, with Kang et al. focusing on minimizing passenger transfer connection headways in Beijing, China, demonstrating that this approach is more effective than solely minimizing waiting time for successful transfers [8]. Yin et al. also addressed the last-train schedules, formulating an objective to balance extended operating hours and associated costs while reducing missed transfers and average waiting times [9].

Beyond passenger time, GAs have been used to optimize operational aspects and overall network efficiency. Ngamchai and Lovell addressed minimizing combined fleet operating costs, in-vehicle passenger time, and waiting time [10]. Vehicle utilization was a key concern for Ataeian et al., who used GAs to maximize simultaneous arrivals and minimize the vehicle count in the bus rapid transit network of Tehran, Iran [11]. Similarly, Naeini, Shafahi, and Taherkhani incorporated the skip-stop operations in their GA-based synchronization for the Tehran subway, aiming to reduce travel times and operating costs while considering passenger waiting time, in-vehicle travel time, and operational expenses [12]. The scope of GA applications extends to diverse network types, including bus networks, as optimized by Bielli, Caramia, and Carotenuto in Parma, Italy, achieving a 90% improvement in a multi-criteria fitness function [13], and by Shafahi and Khani in Mashad, Iran [14]. Integrated systems have also been a focus, with Shrivastava et al. synchronizing bus and train networks with penalties for excessive transfer times [15], and Yu, Yang, and Yao optimizing the multimodal public transport network in Dalian, China, while maintaining the existing fleet [16]. More recently, Wang, Zhou, and Yan applied GAs to synchronize timetables for autonomous buses in Singapore, integrating passenger assignment into the optimization [17].

Comparative studies have often highlighted GAs' strengths. Nachtigall and Voget found that GAs initialized with solutions from a greedy algorithm yielded better results for minimizing passenger waiting time than random initialization [18]. Shafahi and Khani demonstrated that GAs outperformed the Branch and Bound (B&B) algorithm for the bus network synchronization [14]. In a study of the Beijing metro network, Kang et al. compared SA, Tabu Search, B&B, and GA to minimize passenger travel time and schedule deviations, finding GA superior in objective function value and computational speed [19]. Cao et al. also reported that their GA for synchronized and coordinated scheduling optimization outperformed the CPLEX model in speed and solution quality for maximizing synchronized meetings at Beijing metro stations [20]. However, the performance advantage is not without trade-offs; Wang, Li, and Cao, while finding the GA superior to the Gray Wolf Optimizer in solution quality for timetable synchronization (minimizing origin waiting time, transfer waiting

time, and missed connection penalties), noted that GA required significantly more computation time [21]. Further applications include Chen et al., who used GAs to maximize accessible origin-destination pairs [22].

The consistent success of GAs across these varied applications, objective functions, and transport contexts underscores their robustness and utility for solving complex schedule synchronization problems. The literature shows that GAs can effectively handle multi-criteria objectives, diverse operational constraints, and large-scale networks. Given this widespread adoption and proven efficacy, optimizing GA performance itself is a critical research direction. The choice of heuristic parameters within a GA framework significantly influences search efficiency and solution quality. While many studies report successful GA implementations, a detailed investigation into the systematic selection of these parameters for the public transport synchronization problems is essential to harness the full potential of this powerful optimization tool.

When configuring the GA parameters, researchers often set a crossover rate between 50% and 60%. Similarly, a mutation probability of 10% is common because it balances the need to explore new solutions with the need to exploit promising ones within the search space. Regarding population size, research commonly suggests using fewer than 100 chromosomes. This is because, while larger populations can offer more diversity, the resulting increase in computational time often outweighs these benefits.

3 Implementation of GA to synchronize the timetables

The fundamental stages of a GA include evaluating current solutions via a fitness function applied to each population individual, selecting the most fit individuals for propagation, and the reproductive process itself, involving crossover and mutation operators. To address the timetable synchronization problem, the GA population must encode distinct public transport schedule configurations as chromosomes. Next, a fitness-quantification method is needed to support the selection phase. Explicit selection rules must then be established to define the cohort of individuals designated for reproduction in subsequent GA iterations. Furthermore, a crossover procedure that enables the formation of novel individuals from parental pairs must be formulated to underpin the reproduction stage. Finally, a mutation routine tailored to the chosen chromosome is indispensable for mitigating premature convergence to local optima during GA operation. The procedure for encoding timetables as binary chromosomes, along with the corresponding operators, was developed and described in [3].

3.1 Proposed approach to represent the problem

A streamlined method is proposed for representing public transport schedules, particularly effective for the peak-hour timetables where vehicle arrivals at a given stop occur at fixed, predetermined intervals. This common scenario allows for a highly efficient representation. Under this assumption, the entire timetable for a specific transport line can be derived from a single core parameter: the time shift from the service's commencement. This time shift parameter serves as an offset, defining all subsequent arrival times for that line. Consequently, to represent a complete set of timetables across the entire public transport system, a vector of these time shifts can be used, with each element corresponding to a specific transport line.

At its most granular level, a schedule element $S_k^{(\lambda, \nu)}$ for the vehicle ν on the line λ at its k -th sequential position is defined as:

$$S_k^{(\lambda, \nu)} = \langle p_k^{(\lambda, \nu)}, t_k^{(\lambda, \nu)} \rangle, \quad (1)$$

where: $p_k^{(\lambda, \nu)}$ represents the specific public transport line stop (spatial component), and $t_k^{(\lambda, \nu)}$ denotes the moment of arrival of vehicle ν at that stop (temporal component); this dual-component representation is crucial for real-world applications of timetable synchronization as it links geographic locations (public transport stops) with time-based events (vehicle arrivals).

The complete schedule for a vehicle ν on a given line λ , denoted as s_ν , is constructed as a union of these individual schedule elements:

$$s_\nu = \bigcup_{k=1}^{N_s^{(\lambda, \nu)}} S_k^{(\lambda, \nu)} = \bigcup_{k=1}^{N_s^{(\lambda, \nu)}} \langle p_k^{(\lambda, \nu)}, t_k^{(\lambda, \nu)} \rangle, \quad (2)$$

where: $N_s^{(\lambda, \nu)}$ is the total number of scheduled stops for the vehicle ν on the line λ ; an important constraint is that every scheduled position $p_k^{(\lambda, \nu)}$ must belong to the set of defined stops N_λ for line λ : $\lambda: \forall p_k^{(\lambda, \nu)} \in N_\lambda$.

The planned arrival time $t_k^{(\lambda, \nu)}$ for the vehicle ν on the line λ at its k -th scheduled stop is formulated as a linear function of three key parameters:

$$t_k^{(\lambda, \nu)} = t_0 + \phi_\lambda + (k - 1) \cdot \delta_\lambda, \quad (3)$$

where: t_0 represents the system-wide reference start time (e.g., midnight or a defined operational start of the day); ϕ_λ denotes the line-specific initial time shift for line λ , expressed in minutes; this parameter quantifies any offset from the global system start time t_0 for the commencement of service on a particular line; δ_λ signifies the constant interval (headway) between successive vehicle departures on line λ , in minutes; this parameter directly defines the service frequency of line λ and is a critical determinant of service capacity; the term $(k - 1) \cdot \delta_\lambda$ accounts for the cumulative travel time based on the sequential progression through stops.

Since the public transport timetables are typically

established with minute-level precision, the elements of the time-shift vector are integers.

In its simplest application, the public transport schedule synchronization can be achieved by adjusting the initial service start time for each line. These adjustments, central to the schedule synchronization problem, are compactly represented by the vector Ψ :

$$\Psi = \langle \phi_1, \phi_2, \dots, \phi_{N_\Lambda} \rangle, \quad (4)$$

where N_Λ denotes the total number of public transport lines operating within the network.

The vector Ψ serves as a primary control parameter. By manipulating its integer elements, the relative start times of passenger service across all lines in the transport system can be adjusted. This targeted control enables the coordination of passenger service processes, facilitating synchronization with minimal alteration to established operational patterns.

The primary performance metric for assessing the effectiveness of schedule synchronization within the public transport network is the average passenger waiting time $T^{(w)}$ across all public transport stops. This indicator quantifies the cumulative inconvenience and inefficiency passengers experience due to misaligned schedules. Building upon established approaches for synchronization, the $T^{(w)}$ value is proposed to be determined in the following way:

$$T^{(w)} = f(\Psi) = \frac{1}{|D|} \cdot \sum_{\pi \in D} t_\pi^{(w)} \rightarrow \min, \quad (5)$$

where: $t_\pi^{(w)}$ represents the individual waiting time (in minutes) for a passenger π using public transportation; D denotes the set of all passengers or passenger demand instances within the system under consideration, whereas $|D|$ stands for the set's power - the number of elements within a set, representing the total number of intended trips within a transport system.

Minimizing $T^{(w)}$ addresses the core problem of reducing passenger inconvenience and improving the overall efficiency and attractiveness of the public transport system by aligning service provisions more closely with passenger travel needs.

The transport network model, crucial for simulating passenger service based on provided schedules and estimating total waiting time, is thoroughly detailed in [3]. The program implementation of this simulation model is openly accessible on GitHub [23].

The core logic of this simulation model unfolds in the following sequence:

- Given a public transport network graph and the input vector Ψ (representing line-specific initial time shifts), timetables for all lines are calculated using Equation (3).
- Passenger demand for transport services is generated stochastically. Passenger arrival times are determined by a random variable representing inter-arrival intervals. The destination stop for each trip is then

randomly selected or assigned according to a predefined origin-destination matrix.

- For each generated trip, the optimal travel route is determined using Dijkstra's algorithm. If the origin and destination are not on the same line, the transfer nodes are identified for that trip.
- The passenger-servicing process is simulated for each vehicle on every line. The simulation follows the calculated timetable and accommodates the generated passenger demand.
- Upon completion of the simulation, the waiting time for each passenger is computed. Subsequently, the mean waiting time $T^{(w)}$ is aggregated using Equation (5).

Note that the obtained values of $T^{(w)}$ are random due to the stochastic nature of demand generation. Consequently, multiple simulation runs are required to estimate the expected total waiting time.

3.2 Polygon for conducting experimental studies

To demonstrate the computational capabilities of the proposed timetable synchronization approach, a case study was conducted using the public transportation network of Verkhniidniprovsk, Ukraine. This city, located in the Dnipropetrovsk Oblast, was selected for its manageable size and representative urban transport characteristics, making it an ideal environment for validating the developed model without excessive computational overhead.

Verkhniidniprovsk has a population of approximately 17,000 and is served by a compact yet comprehensive public transportation system. The network consists of 5 public transport lines, spanning approximately 80 km. These lines serve 47 bus stops. The fleet comprises 5 vehicles, with one dedicated vehicle per line. Vehicle capacities range from 18 to 50 passengers.

A more granular breakdown of each public transport line in Verkhniidniprovsk's network is presented in Table 1. This detailed information underpins the parameters used in the simulation, enabling the authors to assess how the synchronization methodology can optimize passenger flow and minimize waiting times in a real-world setting.

Within the context of public transport systems, a transfer node is formally defined as any public transport stop served by more than one distinct line, thereby enabling passengers to interchange between different routes. This capability is crucial for passengers navigating the network, allowing them to reach destinations not directly served by a single line.

4 Methodology of studying the influence of GA parameters on synchronization results

The GA performance in optimization is strongly influenced by its heuristic parameters, a critical

factor that requires careful consideration for effective application. Some parameters have a straightforward impact; for instance, increasing the number of generations generally improves results until the algorithm converges on a stable solution. Conversely, other GA parameters are highly context-dependent, directly shaped by the problem being solved. A prime example is the genetic encoding of a solution, such as the number of bits used to represent it. This depends on the problem domain's attributes, such as the total number of lines in a network and the maximum possible headways allowed on those lines.

In the conducted study was analyzed the influence of the four key GA parameters on the effectiveness of timetable synchronization: population size S_p , crossover probability p_c , mutation probability p_m , and the number of attempted mutations per chromosome t_m . To evaluate their impact, the experimental studies define bounds and step sizes for each GA parameter, as detailed in Table 2.

For each experimental series, 300 model replications were executed to ensure a 5% statistical significance level for the obtained results. During each series, the GA parameters not currently under investigation were held constant at the midpoint of their respective evaluated ranges.

To quantitatively estimate the influence of each GA parameter on the optimization results, a regression-based methodology was applied. This approach allows to determine the statistical significance of each parameter's individual or combined impact. If a regression coefficient for a specific GA parameter is statistically significant, it provides evidence that adjusting that parameter's value can measurably improve schedule optimization results.

Specifically, the following linear regression models were utilized, where the explained variable $T^{(w)}$ represents the average waiting time. This metric serves as the primary performance indicator for assessing the quality of the generated public transport schedules, with lower values indicating better optimization. The following regression models were calculated based on the data

obtained within the computational experiment:

$$T^{(w)} = \beta_0 + \beta_s \cdot S_p, \quad (6)$$

$$T^{(w)} = \beta_0 + \beta_c \cdot p_c, \quad (7)$$

$$T^{(w)} = \beta_0 + \beta_m \cdot p_m + \beta_t \cdot t_m, \quad (8)$$

where: β_0 represents the intercept that establishes the baseline for the predicted average waiting time, from which the effects of the GA parameters are then added or subtracted according to their respective coefficients; $\beta_s, \beta_c, \beta_m$, and β_t are regression coefficients that quantify the specific impact of population size, crossover probability, mutation probability, and the number of mutation turns per chromosome, respectively, on the GA's optimization results.

The joint analysis of p_m and t_m in Equation (8) is justified because both parameters define the mutation process's characteristics, frequency, and intensity. Their interplay is particularly crucial for understanding the overall impact of mutation on the GA's ability to explore the solution space and avoid local optima, providing a more holistic view than analyzing them separately.

The statistical significance of each regression coefficient is assessed by examining its confidence interval. For this study, a conventional 5% significance level was used. If a regression coefficient's confidence interval did not include zero, it was deemed statistically significant.

Beyond mere significance, the sign of a significant coefficient indicates the direction of the influence. A negative value for a significant coefficient indicates that increasing the parameter's value would improve the optimization results, as reflected in a desirable reduction in average waiting time. Conversely, a positive value for a significant coefficient suggests that increasing the parameter's value would worsen the GA results, leading to an undesirable increase in waiting time.

Table 1 Characteristics of public transport lines in Verkhniodniprovs'k

Line number	The number of stops (direct + return)	Route length [km] (direct + return)	Vehicle capacity [pax.]
#1	14 + 10	5.95 + 4.8	18
#2	18*	9.34*	50
#3	8 + 8	5.1 + 5.05	18
#4	8 + 8	13.35 + 13.35	38
#5	9 + 9	11.77 + 11.77	38

* Line #2 has a loop route

Table 2 Bounds and step for GA parameters within the experiment

GA parameter	Minimum	Maximum	Step
Population size	20	200	20
Crossover probability	0.1	1.0	0.1
Mutation probability	0.05	0.5	0.05
Mutations per chromosome	1	10	1

5 Results and discussion

In this section, the experimental results are presented, specifically illustrating how the GA parameters influence the average waiting time achieved in the public transport synchronization process. The figures depict the relationships between each GA parameter and three key performance indicators: the smallest, mean, and largest values of average waiting time recorded throughout the entire GA routine.

The largest value of $T^{(w)}$ typically emerges during the GA's initial generations. This early occurrence suggests that this value primarily reflects the GA parameter's immediate impact on the optimization results during the heuristic's starting phase. Conversely, the smallest $T^{(w)}$ value is almost invariably found in the final generation, representing the best possible result discovered and returned by the heuristic procedure. Consequently, its dependence on a given parameter highlights that parameter's critical influence on the optimized solution the GA can produce. Finally, the mean $T^{(w)}$ value serves as a crucial indicator of the GA's overall efficiency. Its dependence on a specific GA parameter explains how that parameter influences the convergence speed of the optimization routine.

Figure 1 illustrates the observed empirical

relationships between $T^{(w)}$ and population size, along with their corresponding regression models. Table 3 presents the regression coefficients and their respective confidence intervals. As shown in Figure 1, a consistent negative correlation emerges between the increasing population size and all three mean waiting-time metrics. This empirically demonstrates that, within the tested range, larger population sizes generally lead to lower average waiting times. Further reinforcing these observations, the calculated confidence intervals confirm the statistical significance of the regression coefficient for all tracked $T^{(w)}$ levels. This significance indicates that increasing the population size positively impacts both the initial and final solutions derived from GA iterations.

Figure 2 illustrates the empirical relationships between average waiting time and varying crossover probabilities. Complementing this graphical analysis, Table 4 provides the numerical details of these relationships, presenting the calculated regression coefficients for the crossover probability. It also includes their respective confidence intervals to evaluate the statistical significance and reliability of the observed impacts on $T^{(w)}$. As follows from Figure 2, the overall trend for the smallest and mean waiting times suggests a slight improvement as the crossover probability

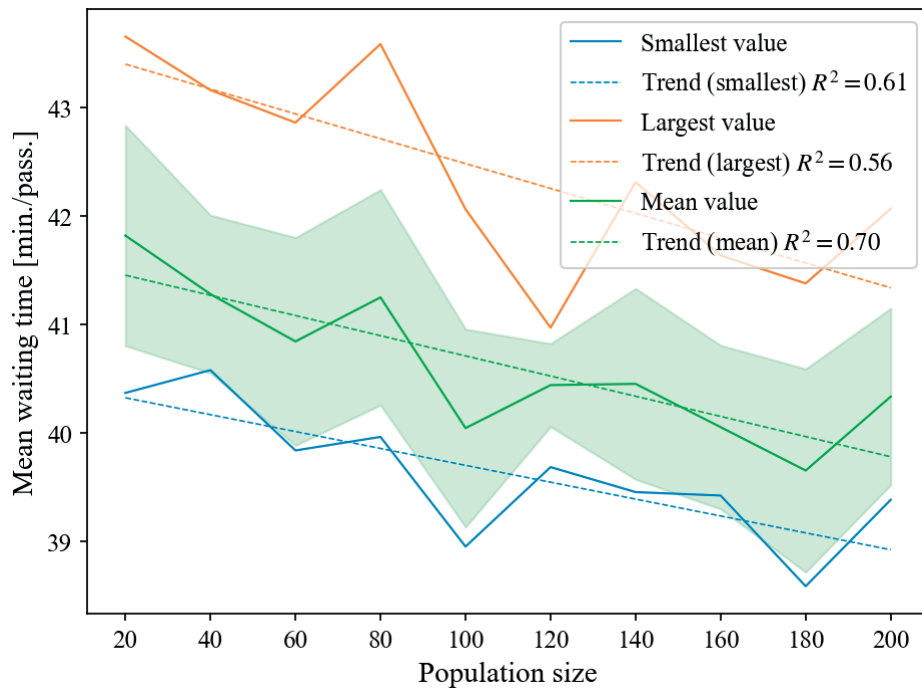


Figure 1 Dependence of the waiting time on the population size

Table 3 Significance of population size in GA performance

Level of the $T^{(w)}$ value	Regression coefficient β_s	Confidence interval	Parameter significance
Smallest	-0.008	(-0.010; -0.005)	True
Largest	-0.011	(-0.015; -0.008)	True
Average	-0.009	(-0.012; -0.007)	True

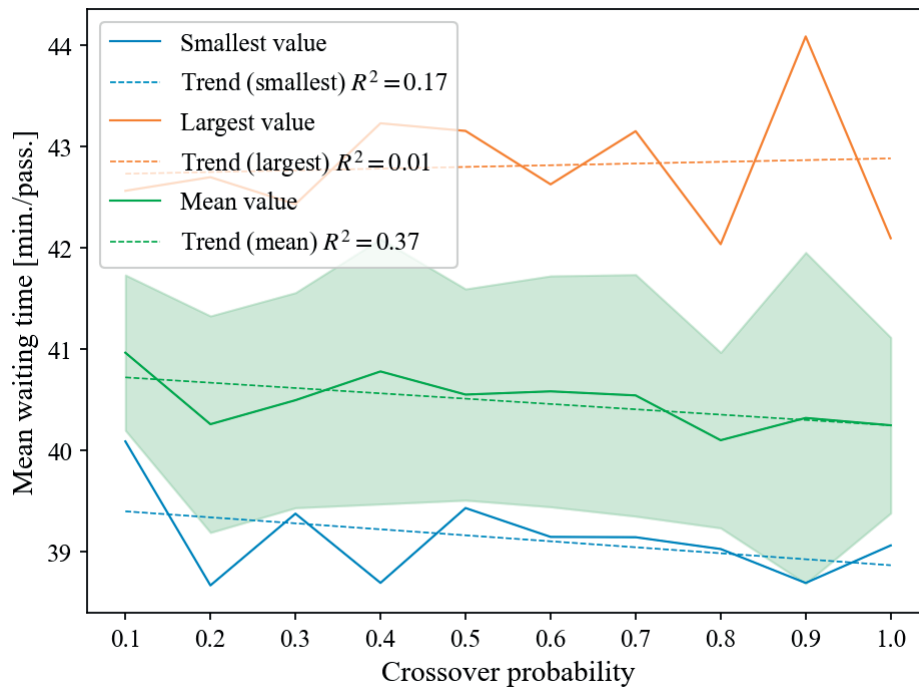


Figure 2 Dependence of the waiting time on the crossover probability

Table 4 Significance of crossover probability in GA performance

Level of the $T^{(w)}$ value	Regression coefficient β_c	Confidence interval	Parameter significance
Smallest	-0.591	(-1.083; -0.100)	True
Largest	0.168	(-0.596; 0.933)	False
Average	-0.526	(-0.785; -0.266)	True

increases. In contrast, the largest waiting time shows a relatively stable or slightly worsening trend, indicating that higher crossover probabilities might not consistently mitigate the initial high waiting times or the variability of less successful runs, even as the best outcomes slightly improve. However, the confidence interval for the coefficient shows that crossover probability does not influence average waiting time at the initial stage of GA, whereas the experimental results confirm a statistically significant impact of this parameter.

Figure 3 provides a visual overview of how the average waiting time varies with mutation probability (the figure presents results for $t_m = 4$). To complement this graphical representation, Table 5 reports the regression coefficients for mutation probability, along with their confidence intervals and statistical significance. As shown in Figure 3, the linear trends have very low determination coefficients R^2 , indicating that mutation probability explains only a small share of the variance in the waiting time metrics across the tested range.

However, a crucial finding emerges when examining the statistical significance of these relationships. As with the crossover probability, the impact of the mutation rate on waiting time during the GA's initial stages (the largest value) is not statistically significant. Conversely, the influence of mutation probability on both the final optimized results (the smallest value) and overall

algorithm performance (the average value) is statistically significant. Notably, the corresponding regression coefficients are positive. Since the objective is to minimize the waiting time, these positive coefficients indicate that increasing the mutation rate leads to a quantifiable increase in passenger waiting time. Consequently, higher mutation probabilities hurt optimization outcomes, hindering the GA's ability to refine solutions as it progresses.

In Figure 4 is presented an examination of the relationship between the average waiting time and the number of attempted mutations per chromosome, with results for $p_m = 0.2$. Table 6 complements this by providing the calculated regression coefficients for t_m and their confidence intervals to assess statistical significance.

As shown in Figure 4, the number of mutations per chromosome appears to have a relatively minor and inconsistent impact on all three mean waiting time metrics. The corresponding trends for these metrics remain largely flat, suggesting that varying t_m within the explored range does not yield substantial linear improvements in the GA's overall operational performance. The significance test for β_t indicates that changes in the number of mutation turns do not significantly affect results during the GA's initial phase, nor do they affect overall performance. However, the

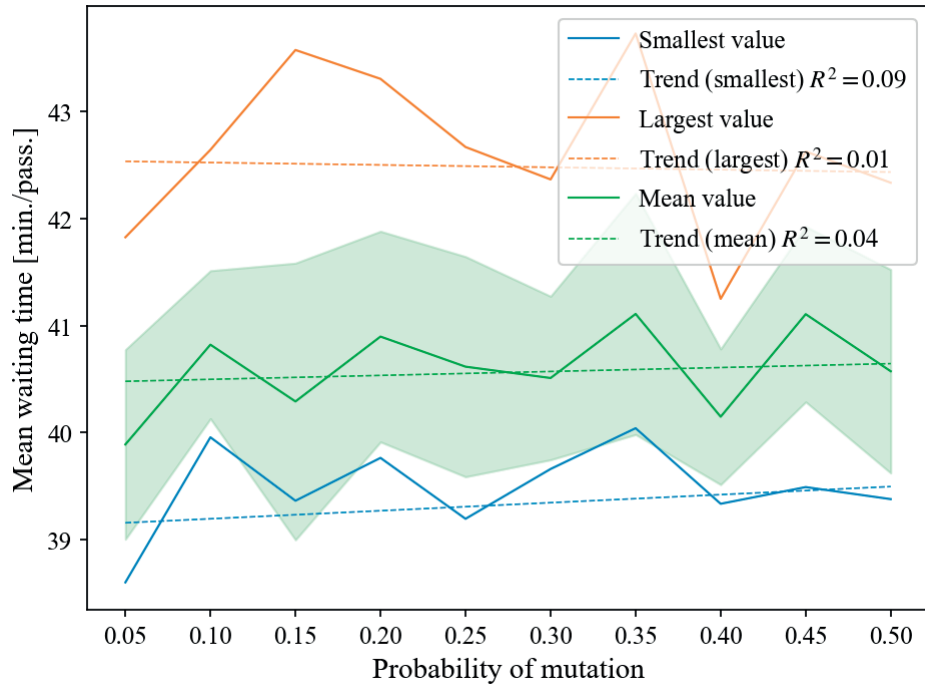


Figure 3 Dependence of the waiting time on the mutation probability

Table 5 Significance of mutation probability in GA performance

Level of the $T^{(w)}$ value	Regression coefficient β_m	Confidence interval	Parameter significance
Smallest	0.753	(0.300; 1.206)	True
Largest	-0.222	(-0.922; 0.478)	False
Average	0.368	(0.055; 0.681)	True

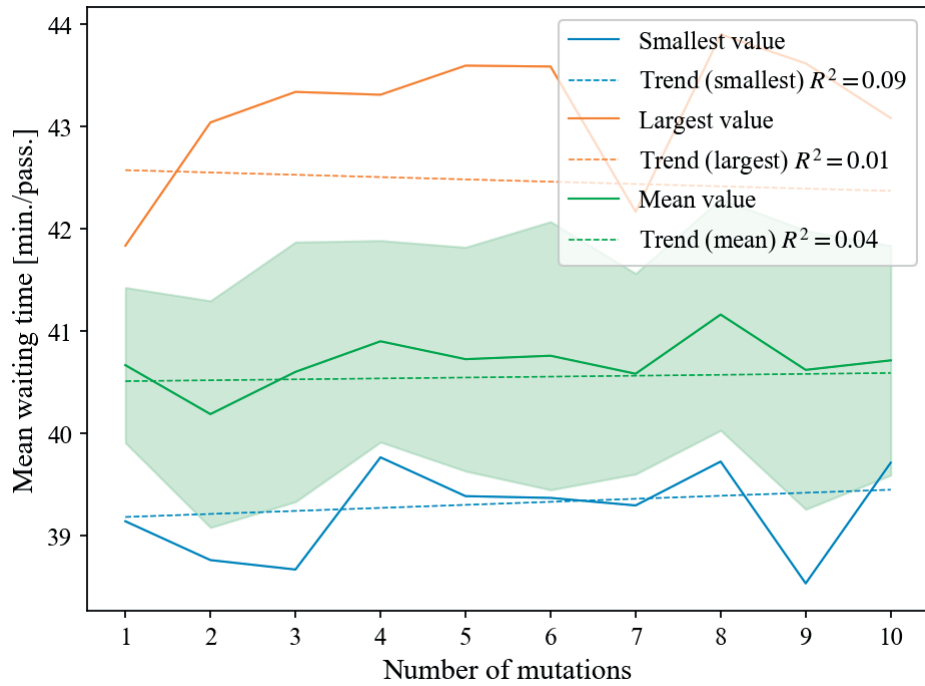


Figure 4 Dependence of the waiting time on the mutation turns

Table 6 Significance of mutation turns in GA performance

Level of the $T^{(w)}$ value	Regression coefficient β_t	Confidence interval	Parameter significance
Smallest	0.030	(0.007; 0.052)	True
Largest	-0.023	(-0.058; 0.012)	False
Average	0.009	(-0.007; 0.025)	False

analysis reveals a statistically significant impact on the GA procedure's results. This implies that while t_m doesn't broadly shape the GA's average performance, it does cumulatively influence the quality of the best solution found.

To address the explained variance, the determination coefficient values have been integrated into Figures 1-4. These values reflect the proportion of variance explained by each parameter. Predictably, lower R^2 values correspond to statistically insignificant relationships, confirming the lack of a meaningful linear trend, while higher values align with significant parameters.

6 Conclusions

In this study was addressed the critical role of heuristic parameter selection in optimizing public transport timetables using GAs. A GA-based heuristic was developed that uses a binary chromosome representation for schedule time-shifts and was integrated with a simulation model to evaluate fitness, with the objective of minimizing passenger waiting times under stochastic demand.

The completed investigation into how GA parameters influence effectiveness yielded several insights for deploying GAs in public transport network synchronization:

- a larger population consistently improved both the initial and final solution quality, significantly enhancing overall GA performance; therefore, using population sizes at the upper bound of the tested range (e.g., 200 individuals) is recommended for optimal results;
- while the crossover probability had minimal impact on early GA stages, it had a statistically significant positive effect on overall performance, suggesting that high crossover rates (e.g., approaching 1.0) are highly beneficial;

- increasing the mutation rate led to poorer solution quality, suggesting a detrimental effect on the GA's ability to converge toward optimal timetables; thus, a minimal mutation probability (e.g., 0.05) is recommended;
- the number of mutation turns had no significant effect on the initial phase of the GA or its overall performance; however, a higher number of mutations had a cumulative effect on the quality of the best solution, indicating that restricting the algorithm to a single mutation per chromosome is preferable.

It is important to acknowledge a genuine limitation of this manuscript: the empirical findings and subsequent parameter recommendations are based on a single, small-city case study. While this setting provided a clear and manageable baseline for evaluating the GA parameters, it does not fully capture the operational complexities and multimodal interactions characteristic of major metropolitan transit networks.

Based on these insights and limitations, future research should test the proposed GA procedure and validate the identified parameter regularities across diverse, larger-scale public transport networks and geographical locations; and investigate dynamic or adaptive parameter-tuning strategies that can adjust GA parameters during the optimization process.

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Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

- [1] KAPICA, D., MELNIKOVA, Y., NAUMOV, V. Synchronization in public transportation: a review of challenges and techniques. *Future Transportation* [online]. 2025, **5**(1), 6 [accessed 2026-06-01]. eISSN 2673-7590. Available from: <https://doi.org/10.3390/futuretransp5010006>
- [2] NAUMOV, V., SAMCHUK, G. Class library for simulations of passenger transfer nodes as elements of the public transport system. *Procedia Engineering* [online]. 2017, **187**, p. 77-81 [accessed 2026-06-01]. ISSN 1877-7058. Available from: <https://doi.org/10.1016/j.proeng.2017.04.352>

- [3] NAUMOV, V., TARAN, I., MELNIKOVA, Y., KAPICA, D. Minimizing passenger waiting in public transport: a genetic algorithm approach to bus schedule synchronization. In: 28th International Scientific Conference Transport Means: proceedings [online] [accessed 2026-06-01]. 2024. p. 91-96. Available from: <https://doi.org/10.5755/e01.2351-7034.2024.P91-96>
- [4] CHAKROBORTY, P., DEB, K., SUBRAHMANYAM, P. Optimal scheduling of urban transit systems using genetic algorithms. *Journal of Transportation Engineering* [online]. 1995, **28**(1), p. 544-553 [accessed 2026-06-01]. ISSN 2473-2907, eISSN 2473-2893. Available from: [https://doi.org/10.1061/\(ASCE\)0733-947X\(1995\)121:6\(544\)](https://doi.org/10.1061/(ASCE)0733-947X(1995)121:6(544))
- [5] WU, J., LIU, M., SUN, H., LI, T., GAO, Z., WANG, D. Equity-based timetable synchronization optimization in urban subway network. *Transportation Research Part C* [online]. 2015, **51**, p. 1-18 [accessed 2026-06-01]. ISSN 0968-090X, eISSN 1879-2359. Available from: <https://doi.org/10.1016/j.trc.2014.11.001>
- [6] TUZUN, A., YILMAZ, S. Transit coordination with heterogeneous headways. *Transportation Planning and Technology* [online]. 2014, **37**(5), p. 450-465 [accessed 2026-06-01]. ISSN 0308-1060, eISSN 1029-0354. Available from: <https://doi.org/10.1080/03081060.2014.912419>
- [7] NIU, H., TIAN, X., ZHOU, X. Demand-driven train schedule synchronization for high-speed rail lines. *IEEE Transactions on Intelligent Transportation Systems* [online]. 2015, **16**(5), p. 2642-2652 [accessed 2026-06-01]. ISSN 1524-9050, eISSN 1558-0016. Available from: <https://doi.org/10.1109/TITS.2015.2415513>
- [8] KANG, L., WU, J., SUN, H., ZHU, X., GAO, Z. A case study on the coordination of last trains for the Beijing subway network. *Transportation Research Part B: Methodological* [online]. 2015, **72**, p. 112-127 [accessed 2026-06-01]. ISSN 0191-2615, eISSN 1879-2367. Available from: <https://doi.org/10.1016/j.trb.2014.09.003>
- [9] YIN, H., WU, J., SUN, H., KANG, L., LIU, R. Optimizing last trains timetable in the urban rail network: social welfare and synchronization. *Transportmetrica B: Transport Dynamics* [online]. 2019, **7**(1), p. 473-497 [accessed 2026-06-01]. ISSN 2168-0566, eISSN 2168-0582. Available from: <https://doi.org/10.1080/21680566.2018.1440361>
- [10] NGAMCHAI, S., LOVELL, D. Optimal time transfer in bus transit route network design using a genetic algorithm. *Journal of Transportation Engineering* [online]. 2003, **129**(5), p. 510-521 [accessed 2026-06-01]. ISSN 2473-2907, eISSN 2473-2893. Available from: [https://doi.org/10.1061/\(ASCE\)0733-947X\(2003\)129:5\(510\)](https://doi.org/10.1061/(ASCE)0733-947X(2003)129:5(510))
- [11] ATAIEAN, S., SOLIMANPUR, M., AMIRIPOUR, S., SHANKAR, R. Synchronized timetables for bus rapid transit networks in small and large cities. *Scientia Iranica* [online]. 2021, **28**(1), p. 477-491 [accessed 2026-06-01]. ISSN 1026-3098, eISSN 2345-3605. Available from: <https://doi.org/10.24200/sci.2019.51501.2220>
- [12] NAEINI, H., SHAFABI, Y., TAHERKHANI, M. Optimizing and synchronizing timetable in an urban subway network with stop-skip strategy. *Journal of Rail Transport Planning and Management* [online]. 2022, **22**, 100301 [accessed 2026-06-01]. ISSN 2210-9706, eISSN 2210-9714. Available from: <https://doi.org/10.1016/j.jrtpm.2022.100301>
- [13] BIELLI, M., CARAMIA, M., CAROTENUTO, P. Genetic algorithms in bus network optimization. *Transportation Research Part C: Emerging Technologies* [online]. 2002, **10**(1), p. 19-34 [accessed 2026-06-01]. ISSN 0968-090X, eISSN 1879-2359. Available from: [https://doi.org/10.1016/S0968-090X\(00\)00048-6](https://doi.org/10.1016/S0968-090X(00)00048-6)
- [14] SHAFABI, Y., KHANI, A. A practical model for transfer optimization in a transit network: Model formulations and solutions. *Transportation Research Part A: Policy and Practice* [online]. 2010, **44**(6), p. 377-389 [accessed 2026-06-01]. ISSN 0965-8564, eISSN 1879-2375. Available from: <https://doi.org/10.1016/j.tra.2010.03.007>
- [15] SHRIVASTAVA, P., DHINGRA, S., GUNDALIYA, P. Application of genetic algorithm for scheduling and schedule coordination problems. *Journal of Advanced Transportation* [online]. 2002, **36**, p. 23-41 [accessed 2026-06-01]. eISSN 2042-3195. Available from: <https://doi.org/10.1002/atr.5670360103>
- [16] YU, B., YANG, Z., YAO, J. Genetic algorithm for bus frequency optimization. *Journal of Transportation Engineering* [online]. 2010, **136**(6), p. 576-583 [accessed 2026-06-01]. ISSN 2473-2907, eISSN 2473-2893. Available from: [https://doi.org/10.1061/\(ASCE\)TE.1943-5436.0000119](https://doi.org/10.1061/(ASCE)TE.1943-5436.0000119)
- [17] WANG, Y., ZHOU, Y., YAN, X. Autonomous bus timetable synchronization for maximizing smooth transfers with passenger assignment. *Expert Systems with Applications* [online]. 2022, **193**, p. 478-492 [accessed 2026-06-01]. ISSN 0957-4174, eISSN 1873-6793. Available from: <https://doi.org/10.1016/j.eswa.2021.116430>
- [18] NACHTIGALL, K., VOGELT, S. A genetic algorithm approach to periodic railway synchronization. *Computers and Operations Research* [online]. 1996, **23**(5), p. 453-463 [accessed 2026-06-01]. ISSN 0305-0548, eISSN 1873-765X. Available from: [https://doi.org/10.1016/0305-0548\(95\)00032-1](https://doi.org/10.1016/0305-0548(95)00032-1)
- [19] KANG, L., WU, J., SUN, H., ZHU, X., WANG, B. A practical model for last train rescheduling with train delay in urban railway transit networks. *Omega* [online]. 2015, **50**, p. 29-42 [accessed 2026-06-01]. ISSN 0305-0483, eISSN 1873-5274. Available from: <https://doi.org/10.1016/j.omega.2014.07.005>
- [20] CAO, Z., CEDER, A., LI, D., ZHANG, S. Optimal synchronization and coordination of actual passenger-rail timetables. *Journal of Intelligent Transportation Systems* [online]. 2019, **23**(3), p. 231-249 [accessed 2026-06-01]. ISSN 1547-2450, eISSN 1547-2442. Available from: <https://doi.org/10.1080/15472450.2018.1488132>

- [21] WANG, Y., LI, D., CAO, Z. Integrated timetable synchronization optimization with capacity constraint under time-dependent demand for a rail transit network. *Computers and Industrial Engineering* [online]. 2020, **142**, 106374 [accessed 2026-06-01]. ISSN 0360-8352, eISSN 1879-0550. Available from: <https://doi.org/10.1016/j.cie.2020.106374>
- [22] CHEN, Y., MAO, B., BAI, Y., HO, T., LI, Z. Timetable synchronization of last trains for urban rail networks with maximum accessibility. *Transportation Research Part C: Emerging Technologies* [online]. 2019, **99**(2), p. 110-129 [accessed 2026-06-01]. ISSN 0968-090X, eISSN 1879-2359. Available from: <https://doi.org/10.1016/j.trc.2019.01.003>
- [23] Class library for simulations of technological processes in a public transport network [online] [accessed 2026-06-01]. Available from: <https://github.com/naumovvs/publictransportnet>