

**SIMULATION-BASED EVALUATION OF SMART CITY
URBAN TRANSPORT INVESTMENTS VIA
EXPERIMENTAL DESIGN**

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Received on August 2, 2025

Presented by Ch. Roumenin, Member of BAS, on November 25, 2025

Abstract

In recent years, the increasingly prominent concept of the smart city has come to the forefront in the world, particularly through efforts aimed at making urban life more inclusive and accessible. In this context, municipalities and public institutions have been planning various investments to ensure equitable access to urban services for individuals with disabilities. However, due to limited public resources, it is crucial that investment decisions be supported by scientific methods. This study addresses investment alternatives aimed at improving public transportation services, specifically municipal bus services, for individuals with disabilities in İzmir, a metropolitan city in Turkey. Based on a selected pilot area within İzmir, the existing transportation system was modelled using simulation software, and multiple investment scenarios were developed on this model. These scenarios were systematically tested using a Design of Experiments (DoE) approach, and the benefits of each scenario were evaluated through the simulation outputs. The results were then statistically analyzed using a one-way ANOVA test. Based on the findings, the most appropriate investment strategy to enhance the transportation experience of individuals with disabilities was proposed.

Key words: smart urban mobility, investment analysis, discrete event simulation, design of experiments, statistical analysis

Introduction. In smart city planning, it is essential to consider not only technological solutions but also social impacts and financial constraints [1,2]. In

<https://doi.org/10.7546/CRABS.2026.01.07>

this regard, the evaluation of investment alternatives that are developed to enhance the accessibility of transportation services for individuals with disabilities must be grounded in scientific methods while taking limited public resources into account. The formulation of various investment scenarios and the analysis of their impacts through simulation-based methods represent an effective and practical approach within decision-support processes [3, pp. 15–38], [4, pp. 55–65].

Simulation techniques offer significant advantages such as process improvement, reduction of travel time and costs, and increased efficiency. Moreover, they enable a comprehensive analysis of existing system resources before any new investment is made [5]. Through simulation, it is also possible to evaluate modelled processes based on performance indicators and to test alternative organizational plans to identify the most suitable configurations [6]. In this way, the aim is to both utilize resources more efficiently and enhance the quality of service.

The DoE methodology is a powerful tool for systematically examining multiple factors and optimizing process performance. The advantages of factorial designs, noting that such designs allow for the measurement not only of main effects but also of interactions between factors has been emphasized [7, pp. 171–210]. This enables the identification of the most critical influences and supports the efficient allocation of resources.

In this study, smart city-based investment alternatives aimed at improving the accessibility of the public transportation system for individuals with disabilities in İzmir, a metropolitan city in Turkey, were quantitatively evaluated. Using real data, the existing transportation system was modelled with Arena Rockwell Simulation software [8], and the developed investment scenarios were systematically tested through the DoE approach. The performance of each scenario was statistically compared using one-way ANOVA analysis via Minitab software [9], and the differences between scenarios were thoroughly assessed based on confidence interval results. This study aims to provide a guiding example that contributes both to the analytical evaluation of smart city investments and to the enhancement of urban accessibility for individuals with disabilities.

Modelling the public transportation process. In simulation-based modelling studies, the process typically begins with system definition, followed by model formulation, data collection, model construction in a software environment, and validation of the model. In the modelling phase of this study, a simulation model was developed first to represent and analyze the current state, and subsequently to assess the system after the implementation of proposed investments [4, pp. 66–70].

In the simulation and modelling phase of this study, a simulation model was developed first to represent and analyze the current situation, and subsequently to assess the new state after the implementation of proposed investments. The travel processes of individuals with disabilities using municipal buses in İzmir which is a major metropolitan city were modelled in the simulation software, covering

the journey from arrival at the bus stop to disembarkation from the bus. Given that modelling İzmir's entire public transportation network, consisting of nearly 2000 vehicles, would increase complexity, a pilot region and pilot bus routes were selected for the study.

In the simulation model developed for the transportation process, the independent variables included the number of buses assigned to each route, bus departure times, the number of vehicles allocated to specific routes at certain times, bus stop locations, and the number of stops. The dependent variables in the system were the waiting time of individuals with disabilities for the bus at the stop, the time elapsed from the bus's arrival at the stop until the individual boards, the boarding duration, and the disembarking duration. Fixed variables used in the model construction included information such as the bus used by the individual with a disability, the boarding date and time, and the bus stop utilized by the individual. The data employed were obtained in real time from the public institution responsible for providing public transportation services in the city where the study was conducted.

In the computer-based modelling phase, bus routes were modelled first. Bus schedules are planned specifically for different time periods throughout the day. Accordingly, time intervals, the headway between bus arrivals, and the capacity of each bus route were defined within the software. During the bus route planning stage, stops where passengers board and alight, as well as the queues formed at these stops, were defined in the simulation model by creating routes based on the predetermined bus lines.

Disabled passengers arrive at the designated stops along the defined bus routes and board the buses from these stops. Passenger arrival rates at each stop vary according to different time intervals. Because the time between arrivals of two passengers continuously fluctuates, these values were analyzed using the input analyzer feature of the Arena simulation software, and the resulting stochastic values were incorporated into the simulation model as input data. During input analysis, passenger arrivals at a specific stop were sequenced separately for each time interval within the relevant month, and the times between consecutive arrivals were calculated. These inter-arrival time samples were then imported into the software, and the input analysis was performed based on the results of the Pearson chi-square test and the Kolmogorov–Smirnov test. The Pearson chi-square test evaluates the magnitude of differences between observed and expected frequencies to assess whether the data set fits a specific probability distribution. The Kolmogorov–Smirnov test measures the goodness of fit by considering the maximum difference between the empirical distribution function and the theoretical distribution function. The Pearson chi-square test statistic is expressed in Equation (1), while the Kolmogorov–Smirnov test is represented by Equation (2)

[10, pp. 696-698].

$$(1) \quad x^2 = \sum_{i=1}^k \frac{(O_i - E_i)^2}{E_i}$$

$$(2) \quad D = \max |F_n(x) - F(x)|.$$

In Equation (1), the parameters include the observed frequency (O_i), the expected frequency (E_i), and the number of classes (k). In Equation (2), the maximum absolute difference (D) is calculated using the empirical cumulative distribution function ($F_n(x)$) and the theoretical cumulative distribution function ($F(x)$). Based on the results of these tests, the most appropriate distribution functions were identified, and the parameters of these distributions were defined as input data in the Arena simulation model.

To model the transportation process flow of passengers with disabilities, a simulation model was developed in the Arena software. After defining the bus lines used in the transportation process, bus routes, stops where buses pick up and drop off passengers, passenger arrival frequencies at these stops, and the durations involved in all these stages, the model was designed to simulate buses travelling along specified routes, passengers boarding and alighting the buses, and buses repeating the same cycle upon completing their routes. The loop model established to represent the flow is illustrated in Fig. 1.

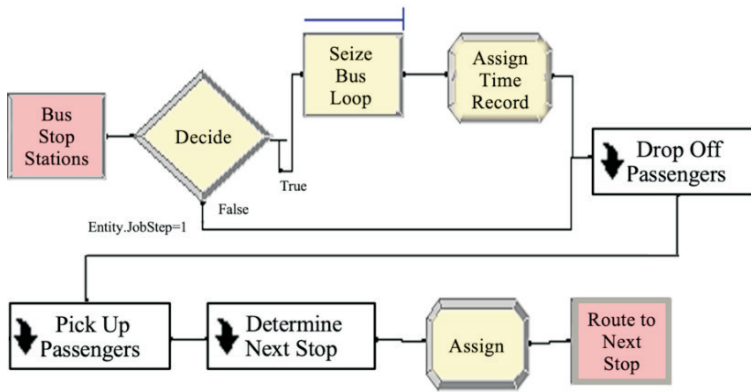


Fig. 1. Transportation simulation loop model

The targeted improvements in smart city investments planned by the public institution for public transportation focus on reducing both the time buses spend within the system and the time passengers spend travelling. Accordingly, the performance metrics used in the analysis and results related to the model in this study are defined as “average bus trip duration” and “average passenger travel time.” These performance measures, expressed as numerical values, are critical

in guiding investment decisions. The average bus trip duration refers to the time elapsed from when a bus enters the system until it completes a full circuit of its route. The average passenger travel time denotes the duration from when a passenger arrives at the bus stop until they disembark from the bus.

Once the model has been developed in the computer program, the question of how many replications should be run becomes significant. For the developed simulation model, the appropriate number of replications was determined to be 10 based on Equation (3).

$$(3) \quad \left(\frac{h_0}{h_1}\right)^2 \cdot p_0 = p_1.$$

The additional number of replications (p_1) is calculated using the parameters of the current half-width value (h_0), the desired half-width value (h_1), and the current number of replications (p_0) in Equation (3).

To proceed with the study by conducting analyses on the developed simulation model, it is essential to ensure the model's accuracy. One way to establish model validity is by comparing the performance measures in the model with those of the real system after modelling the system [11]. In this study, a one-sample t -test was applied to examine whether the difference between the simulation model and the real system is statistically significant. This test allows the comparison of the mean output obtained from the simulation model with a fixed value observed in the real system. The test statistics are expressed by Equation (4).

$$(4) \quad t = \frac{\bar{x} - \mu_0}{s/\sqrt{n}}.$$

In Equation (4), the parameters include the average value obtained from the simulation model ($\bar{x}$), the true system value (μ_0), the standard deviation of the simulation outputs (s), and the number of replications (n). The calculated t -value is compared with the critical t -value determined based on the degrees of freedom for a given significance level ($\alpha = 0.05$). In this context, the hypotheses H_0 (there is no difference between the simulation model and the real system) and H_1 (there is a difference between the simulation model and the real system) are tested.

According to the decision rule, if the calculated t -value is less than the critical t -value, H_0 hypothesis is not rejected, and it is accepted that the simulation model statistically represents the real system. Otherwise, if this condition is not met, H_0 is rejected, indicating that the model produces results that differ significantly from the real system [12, pp. 548–550].

Comparisons prepared separately for the two selected criteria between the developed simulation model and the real system are presented in Tables 1 and 2. According to the one-tailed t -distribution table, the critical value at a 0.05 significance level with 9 degrees of freedom is 1.833. Since the calculated t -values

for the simulation models of the two bus routes examined are less than 1.833, H_0 hypothesis, indicating that the simulation model is consistent with the real system, is accepted.

T a b l e 1

Statistical comparison of the simulation model and the real system

a. *t*-test based on the result variable “daily number of bus trips”

Bus route*	Real system result (μ)	Simulation result ($\underline{x}$)	$\mu - \underline{x}$	Standard deviation/ Degree of freedom $(S/\sqrt{n})^2$	<i>T</i> value $(\mu - \underline{x})/(S/\sqrt{n})^2$
304	158	154	4	2.22	1.8
72	100	98	2	1.7	1.17

b. *t*-test based on the result variable “number of passengers entering the system”

Bus route*	Real system result (μ)	Simulation result ($\underline{x}$)	$\mu - \underline{x}$	Standard deviation/ Degree of freedom $(S/\sqrt{n})^2$	<i>T</i> value $(\mu - \underline{x})/(S/\sqrt{n})^2$
304	1105	1303	198	199.9	0.99
72	1017	1139	122	194.4	0.63

*The pilot bus routes selected in the region where the simulation model was developed are numbered 304 and 72.

To reduce waste in transportation and ensure safe and accessible travel, it has been decided to invest in an external speaker system, a smart information system, and a smart information display that will provide audio-visual information on buses and at bus stops. An integrated decision model has been developed to select the routes and stop locations where these applications are to be implemented [13], using data mining and multi-criteria decision-making techniques based on the expected benefit rates.

The reductions in process times resulting from the implementation of the investments, as well as the overall effects on the system and changes in the transportation process, were analyzed in the simulation model by designing experiments.

Design of experiments in simulation application. In this study, while conducting the design of experiments to measure the impact of investment alternatives on the performance of the public transportation system, factors affecting the process were varied, and the variability of key performance indicators at the end of the process was assessed [14, pp. 67–74]. During the design of experiments phase of this study, an appropriate experimental design was developed by following the stages illustrated in Fig. 2, and experiments were conducted to evaluate the results.

The planned investments aim to reduce both the travel time for individuals with disabilities using public transportation and the time buses take to complete

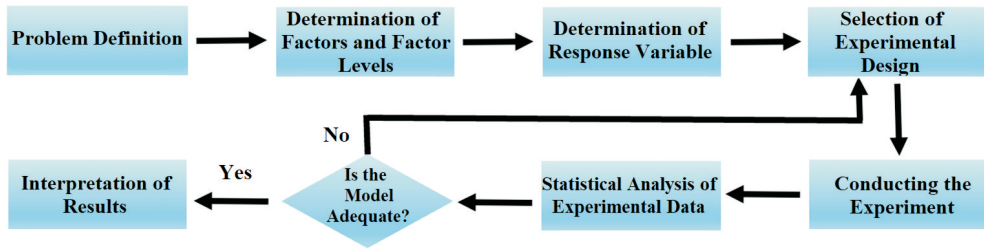


Fig. 2. Stages of the design of experiments

their routes. To determine the impact of these investments on the defined performance metrics and the critical variables that influence decision-making, a design of experiments was conducted. This approach provides guiding analyses to help decide which investment or combination of investments should be implemented [15].

Based on the defined problem, the factors and factor levels to be used in the experiment were determined. In the case of implementing the planned investments, the values expected to vary are the walking and disembarking times of passengers with disabilities. In the designed experiment, the factors influencing these variables are the planned investments themselves. Therefore, the factors defined in the experiment are set at two levels: implementation of the investment and non-implementation.

In the experiment, the variables affected by these factors influence the outcome at varying rates depending on the type of investment and the class of passengers with disabilities. When each type of investment is implemented, the results are reassessed, and new numerical values are generated. Based on the expected benefit rates of the planned investments, individuals with disabilities are classified into three groups. As a result of the proposed investments, walking and disembarking times for each disability class vary at different rates.

Based on the benefit ratio of the planned investments, individuals with disabilities have been categorized into three groups: visually impaired, hearing impaired, and other disabilities. As a result of the planned investments, the walking time from the stop to the bus and the disembarking time vary at different rates for passengers in each disability class.

Output variables are the main performance indicators measured and evaluated at the end of the experiment. Defining the output variable is important in the experimental design process to ensure that the results obtained can be interpreted in a meaningful and accurate way. The output variables to be monitored in the designed experiment were identified as the bus route completion time (1st performance measure) and the total travel time of the disabled passenger (2nd performance measure). With the implementation of investments and the resulting variability in factors affecting the outcomes, the numerical values of these two output variables were also expected to change.

In this experiment, where the factors, variable values, and outputs were defined, a framework was designed to evaluate the outcomes depending on whether the planned investments are implemented or not. Considering the efficient use of public resources, eight different scenarios were developed for cases in which all or some of the investment items are implemented. For each investment scenario, the simulation model was run with 10 replications, and the result values of the output variables obtained in each replication were used to analyze the statistical differences between the investment alternatives. A one-way ANOVA test was applied in the analysis to determine whether there was a statistically significant difference between the scenarios. In addition, if the investment scenarios are implemented, the improvement rates in the specified performance criteria, compared to the current situation, were also evaluated.

The experiments of the developed simulation model were carried out using the “Process Analyzer” module of the Arena software. In the conducted experiment, a total of 23 experimental designs were created by generating different combinations based on the types of investments and the various cases in which the three investments were implemented either individually or in combination.

As a control parameter in the experimental setup, the variables expected to be affected in the case of implementing the investments, namely, the time it takes for a passenger with disabilities to walk from the bus stop to the bus after it arrives, and the time it takes to get off the bus once it stops at the destination stop, along with the output parameters identified in the previous step, were included in the experimental setup. After entering the relevant time values defined for each scenario, the model was run for 10 replications.

To analyze whether there is a statistical difference between the scenarios, a one-way ANOVA test, which is used to examine the significant difference between the means of independent groups, was applied. The test statistics are expressed by the following equation [12, pp. 550–555].

$$(5) \quad F = \frac{SSB/(k-1)}{SSW/(N-k)}, \text{ where } SSB = \sum_{i=1}^k n_i (\bar{X}_i - \bar{X})^2$$

$$\text{and } SSW = \sum_{i=1}^k \sum_{j=1}^{n_i} (X_{ij} - \bar{X})^2.$$

Equation (5) includes the following parameters: SSB (sum of squares between groups), SSW (sum of squares within groups), k (number of groups), n (total number of observations), $\bar{X}_i$ (overall mean of the i -th group), $\bar{X}$ (overall mean of all data), X_{ij} (the j -th observation in the i -th group).

In the statistical analysis of the experimental results for the scenarios involving eight different combinations of investment types applied either jointly or separately, the 95% confidence interval values for each scenario were calculated using the Minitab software.

Analysis results. In this study, the p -values of the analyzed scenarios were found to be less than 0.05, indicating that the differences between the scenarios are statistically significant. It was thus concluded that the scenarios differ statistically from one another. However, pairwise comparisons of the scenarios revealed that some scenarios do not exhibit statistically significant differences. Table 2 presents the scenario numbers, the investment decision statuses coded as 0 or 1 according to the experimental design, the improvement rates compared to the current situation upon implementation of the scenarios, and the statistical differences between scenarios indicated by letter codes. Scenarios marked with the same letter do not differ from each other, whereas those marked with different letters show statistically significant differences. If a scenario is marked with two distinct letters, it implies that the scenario does not differ significantly from either of the groups represented by those letters. In Table 2, the following are defined: 1st investment item (external speaker system), 2nd investment item (in-vehicle smart information screen), 3rd investment item (smart stop information system), 1st performance metric (average bus trip duration), and 2nd performance metric (average travel time).

T a b l e 2
Scenario comparison table based on experimental results

Scenario no	1. Invest- ment item	2. Invest- ment item	3. Invest- ment item	Average improve- ment rate	Scenario group categorized by the 1st performance indicator	Scenario group categorized by the 2nd performance indicator
1	0	0	0	0	A	A
2	1	0	0	6.78%	C	B, C
3	0	0	1	2.99%	B	A, B
4	0	1	0	5.58%	C	B, C
5	0	1	1	7.68%	E	B, C
6	1	1	0	10.11%	F	C
7	1	0	1	7.34%	D	B, C
8	1	1	1	10.77%	F	C

According to the analysis results, the outcome values of Scenarios 6 and 8 are proportionally close to each other, and both demonstrate greater time savings and improvement rates compared to the other scenarios.

When considering only the “average passenger travel time” performance metric, no statistically significant differences are observed among Scenarios 2, 4, 5, and 7. However, when the “average bus trip duration” metric is also considered, differences emerge across all scenarios, with Scenarios 6 and 8 providing the greatest time savings.

Conclusion. Investments to enhance accessibility should be evaluated through analytically grounded methods that ensure the efficient and effective use of public resources. This study provides a scientifically based framework for decision-makers by assessing potential interventions to improve the transportation experience of individuals with disabilities.

The study analysed the benefits of investment alternatives tailored to the mobility needs of passengers with disabilities through simulation-based modelling. While implementing all proposed investments would be ideal, a detailed benefit analysis is crucial for informed decision-making under cost constraints and for ensuring the efficient allocation of public resources. The results demonstrated how different scenarios could improve both passenger travel times and bus service durations, with statistically significant differences and benefit ratios clearly identified.

When the projected improvements from the pilot area are extrapolated to the entire city of İzmir, Scenario 8, which includes all investment items, yields an estimated reduction of 1003 hours (0.46%) in daily bus travel time, while Scenario 6 achieves 0.43%. During implementation, the anticipated travel-time improvement is derived as a model output by integrating the proposed investments into the simulated system relative to the existing condition. The input time values were determined using the method study technique. Although the improvement appears modest in percentage terms, it represents a considerable cumulative gain. Beyond generating institutional efficiency, the project primarily aims to create social value for individuals with disabilities. Therefore, Scenario 8 is recommended as the optimal option, while Scenario 6 remains a viable alternative when budget constraints exist, and a cost-benefit comparison between the two may guide final investment decisions.

The combined use of simulation and design of experiments techniques enables cost-effective and scientifically grounded evaluations in pre-investment decision-making. This study employed an integrated approach that combines simulation-based modelling, systematic experimental design, and statistical analysis. Through this methodology, the research contributes to the literature on data-driven planning, inclusive transportation solutions, and efficient resource utilization within the framework of smart city development. Moreover, it provides a guiding framework for public institutions implementing projects for disadvantaged groups by offering technical and methodological tools applicable to investment decisions aimed at improving efficiency and financial performance.

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