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Deciphering the Dynamics of Bus Rapid Transit Delays: A Decision Trees and Bayesian Networks Approach for Istanbul's Metrobus System

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ABSTRACT

Public transportation systems are vital components of urban infrastructure, shaping mobility and development. The emergence of Bus Rapid Transit (BRT) systems offers a promising solution to challenges faced by traditional bus services. However, delays within BRT systems can compromise their efficiency and reliability. The goal of this study is to investigate and analyze the critical factors influencing delays in Bus Rapid Transit (BRT) systems, specifically focusing on the Istanbul Metrobus, in order to provide actionable insights for optimizing operations and enhancing service reliability in BRT operations. Decision Trees identify critical parameters affecting delays, while Bayesian Networks elucidate causal dependencies among variables. The proposed Bayesian Precedence Network integrates these methodologies. This study employed a range of diverse data sources analyzed through advanced software tools like GeNIe Modeler. The results underscore the effectiveness of decision analysis in quantifying uncertainties and assessing critical factors that inform transit planning and optimization. The findings reveal that a passenger occupancy rate of 43% results in a 76% probability of no delays, while high traffic flow decreases this probability to 55%. Conversely, clear weather conditions enhance this probability to 80%, whereas rainy conditions and non-optimized operational efficiency heighten the risk of delays. Overall, this study provides a blueprint for addressing public transportation challenges, empowering transportation planners and policymakers to create more efficient and reliable transit networks.

Keywords: *Bus Rapid Transit, Decision Tree, Bayesian Network, Public Transportation, Delay*.

ABSTRAK. Kajian Keterlambatan Bus Rapid Transit *Dengan Pendekatan Pohon Keputusan Dan* Bayesian Networks *Pada Sistem Metrobus Istanbul. Sistem transportasi umum merupakan komponen penting dari infrastruktur perkotaan yang mendorong mobilitas dan pembangunan. Sistem Bus Rapid Transit (BRT) menawarkan solusi untuk mengatasi tantangan yang dihadapi oleh layanan bus tradisional. Namun, keterlambatan dalam sistem BRT dapat mengganggu efisiensi dan keandalannya. Tujuan dari penelitian ini adalah untuk menganalisis faktor-faktor kritis yang mempengaruhi keterlambatan dalam sistem Bus Rapid Transit (BRT), khusunya pada sistem Metrobus Istanbul. Studi ini dapat memberikan wawasan yang dapat ditindaklanjuti untuk mengoptimalkan operasi dan meningkatkan keandalan layanan BRT. Pohon Keputusan mengidentifikasi parameter kritis yang mempengaruhi keterlambatan, sedangkan Bayesian Networks dapat menjelaskan ketergantungan sebab akibat antar variabel. Bayesian Precedence Network yang diusulkan mengintegrasikan kedua pendekatan ini. Penelitian ini menggunakan berbagai sumber data yang beragam yang dianalisis dengan GeNIe Modeler. Hasil penelitian menunjukkan bahwa analisis keputusan efektif digunakan untuk mengukur ketidakpastian dan menilai faktor-faktor penting yang menjadi dasar perencanaan dan optimalisasi angkutan umum. Hasil penelitian selanjutnya adalah dengan tingkat keterisian penumpang sebesar 43% dapat menghasilkan probabilitas 76% untuk tidak ada keterlambatan, namun arus lalu lintas yang tinggi* *dapat menurunkan probabilitas tersebut menjadi 55%. Sebaliknya, kondisi cuaca yang cerah meningkatkan probabilitas tersebut menjadi 80%, sedangkan kondisi hujan dan efisiensi operasional yang tidak optimal meningkatkan risiko keterlambatan. Secara keseluruhan, studi ini memberikan cetak biru untuk mengatasi tantangan transportasi publik, memberdayakan perencana transportasi dan pembuat kebijakan untuk menciptakan jaringan angkutan umum yang lebih efisien dan dapat diandalkan.*

Kata Kunci: *Bus Rapid Transit, Pohon Keputusan, Bayesian Network, Transportasi Publik, Keterlambatan.*

1. INTRODUCTION

Public transportation systems play a pivotal role in shaping urban development and mobility (Vuchic, 2007). As cities grapple with increasing vehicular traffic, the need for efficient and reliable transportation options becomes paramount (Levinson et al., 2002). Traditional bus services often face challenges such as long waits, and overcrowding, leading to a perception of low-quality service in response to these issues, Bus Rapid Transit (BRT) systems have emerged as a viable alternative (Vuchic, 2007). BRT combines the advantages of light rail systems with the flexibility and cost-effectiveness of rubber-tyre vehicles. However, delays within BRT systems can significantly impact their efficiency, reliability, and overall effectiveness. Understanding the critical factors that contribute to these delays is essential for optimizing BRT operations (Levinson et al., 2002). Studying delays in BRT systems is crucial for ensuring that these systems meet their intended goals of efficiency and reliability, as delays can lead to reduced ridership and user dissatisfaction. By identifying the factors causing these delays, planners can implement targeted solutions that improve overall system performance, optimize resource allocation, and enhance urban mobility, contributing to more sustainable transportation options.

Istanbul, Turkey, currently employs a BRT system, which has become an essential part of the city's transportation network (Istanbul Metropolitan Municipality, 2023). The Istanbul Metrobus system stands as a vital artery in the city's transportation network, seamlessly connecting neighborhoods across the European and Anatolian sides. Launched in 2007, this BRT system offers several advantages, including dedicated lanes that bypass traffic congestion (Istanbul Metropolitan Municipality, 2023). Commuters rely on the Istanbul Card (Istanbul kart) for access, which works across all public transport modes. However, like any urban transit system, the Metrobus faces delays. Understanding the critical parameters affecting these delays—such as traffic flow, operational efficiency, and weather conditions—is essential for optimizing its performance (Levinson et al., 2002).

The study focuses on examining the factors that contribute to delays in BRT systems. Using advanced analytical techniques, specifically Decision Trees and Bayesian Networks, this research seeks to identify the various parameters that influence these delays. These methodologies clarify the relationships among these factors:

1. Decision Trees

   Decision Trees stand out as robust instruments for both classification and regression analyses. They create a hierarchical structure of decisions based on input features, allowing us to discern patterns and relationships (Xu et al., 2013). In our context, Decision Trees will help identify the most influential parameters affecting BRT delays. By branching through various conditions, we can pinpoint critical factors such as traffic congestion, weather conditions, and operational inefficiencies (Xu et al., 2013).
2. Bayesian Networks

   Bayesian Networks provide a probabilistic framework for modeling complex systems (Koller & Friedman, 2009). They capture causal dependencies among variables, allowing us to assess uncertainty and make informed decisions. In our study, Bayesian Networks will map out the cause-and-effect relationships between BRT delay parameters. By considering multiple risk factors simultaneously, we gain a holistic view of the system (Koller & Friedman, 2009). The proposed model, aptly named the Bayesian Precedence Network, integrates these networks with precedence relationships (Koller & Friedman, 2009). Project managers can leverage this approach to estimate project completion time, total slack, and other critical scheduling parameters. It equips them with actionable insights to mitigate delays and enhance project outcomes.

The fusion of Decision Trees and Bayesian Networks empowers transportation planners and policymakers to proactively address BRT delays (Xu et al., 2013). By understanding the interplay of critical parameters, we pave the way for more efficient and reliable public transit systems. This study aims to investigate and analyze the critical factors influencing delays in BRT systems, with a specific focus on the Istanbul Metrobus. By employing advanced analytical techniques, namely Decision Trees and Bayesian Networks, the study seeks to:

1. Identify and quantify the key parameters contributing to delays, such as operational efficiency, and weather conditions.
2. Develop a comprehensive understanding of the cause-and-effect relationships among these factors, facilitating a holistic view of the BRT system's performance.
3. Provide actionable insights for transportation planners and policymakers to optimize BRT operations, enhance service reliability, and improve user satisfaction.
4. Ultimately, this research aims to contribute to the development of more efficient and sustainable urban transportation systems by addressing the challenges posed by delays in BRT operations.

The findings of this research hold significant implications for urban transportation planning and policy. By identifying and analyzing the critical factors contributing to delays in BRT systems, the study aims to:

1. Enhance System Efficiency: Understanding the dynamics behind delays allows for targeted interventions that can streamline operations, reduce travel times, and increase the overall efficiency of BRT systems.
2. Improve Reliability: Insights gained from the study can lead to improved scheduling and resource allocation, thereby enhancing the reliability of BRT services. This, in turn, can boost rider confidence and increase public transportation usage.
3. Elevate User Satisfaction: By addressing the root causes of delays, the research can contribute to a better user experience, reducing frustrations associated with long wait times and overcrowding. Higher satisfaction rates can lead to increased ridership and a stronger public transit system.
4. Support Sustainable Urban Development: Optimized BRT operations can contribute to more sustainable urban mobility solutions, helping cities manage traffic congestion and reduce environmental impacts associated with private vehicle use.
5. Inform Policy Decisions: The methodologies employed in this study—Decision Trees and Bayesian Networks—provide a framework for ongoing analysis and decision-making. Policymakers can use these insights to develop data-driven strategies that address current challenges and anticipate future needs in urban transportation.

Overall, the research findings can serve as a valuable resource for transportation planners and city officials, ultimately contributing to the development of more efficient, reliable, and sustainable public transit systems.

2. LITERATURE REVIEW

A study (Halyal et al., 2022) investigates the travel time characteristics within the Hubli-Dharwad BRT system. By comparing it with heterogeneous traffic lanes, researchers aim to understand the impact of dedicated BRT corridors on bus operations. Notably, trial running speeds closely align with measured free-flow speeds, indicating the effectiveness of segregated BRT lanes. However, delays primarily occur at stations due to factors like bus bunching and dwell time. Addressing these station-related delays is crucial for optimizing BRT performance.

An integrated optimization model is proposed to enhance BRT operations. By adjusting BRT scheduling, signal timing, and dwelling strategies, the model aims to reduce passenger delays. Passenger demand fluctuations and bus operation uncertainties are considered. The results demonstrate significant improvements in mean and maximum passenger travel time compared to conventional strategies. Coordinated efforts in scheduling and signal management can mitigate delays and enhance BRT efficiency (Wang et al., 2022). In other research (Wu et al., 2023) focuses on optimizing signalized intersections within BRT systems. Recognizing the need to accommodate both BRT buses and regular traffic, the research formulates signal delay prediction models. By fine-tuning signal offsets, delays at intersections can be minimized. Efficient signal coordination is essential to ensure smooth BRT flow and reduce passenger waiting times.

In addition, next study (Jayakumar & Maji, 2023) delve into commuters' safety and comfort perceptions within the bustling transportation network of Maharashtra, India. The challenges faced by commuters are multifaceted, encompassing safety, security, comfort, and convenience. Specific issues include concerns about harassment, theft, fear of COVID-19 transmission, rude staff behavior, rash driving, and overcrowding. Notably, socio-economic, and trip-related characteristics significantly influence commuters' perceptions. A decision tree analysis reveals intriguing patterns: female commuters prioritize safety and security, while frequent public transit users and those from low- and middle-income backgrounds emphasize both safety and comfort. To enhance service quality, the study recommends implementing speed monitoring for public transport, improving station accessibility, enhancing surveillance systems, adjusting fleet sizes, and revising operating schedules. These findings offer valuable insights for optimizing public transportation in a developing economy.

A study (Kavalov, 2019) focused on NJ Transit, researchers aimed to predict delays using decision trees. They scraped real-time data on every stop made by NJ Transit/Amtrak trains, updating it every minute to track train delays. Challenges faced by commuters include safety, security, comfort, and convenience. Specific issues range from harassment and theft to fear of COVID-19 spread and rude staff behavior. Decision tree analysis revealed that factors like train ID and seasonal variations (Summer vs. Winter) significantly influence lateness. While initial results were less impressive, further research and feature engineering could enhance delay prediction models for public transportation.

Another study (Shoman et al., 2020) proposes a deep learning-based framework for predicting bus delays at the network level. Leveraging large, heterogeneous bus transit data (GTFS) and vehicle probe data, the framework employs entity embeddings to simultaneously fit functions and learn patterns from both categorical and continuous data streams. Accurate delay prediction enhances reliability and optimizes travel structures in urban transit networks. Analyzing customer satisfaction surveys, researcher's (de Oña et al., 2016) study distinguishes passenger groups based on service quality perceptions. Decision trees identify the most important service quality attributes influencing passengers' overall evaluations. Understanding these attributes can guide improvements in public transportation service quality, enhancing commuter satisfaction.

A stochastic model is presented for predicting the propagation of train delays based on Bayesian networks by another researcher (Corman & Kecman, 2018). This method efficiently represents and computes the complex stochastic inference between random variables. The model allows for updating probability distributions and reducing the uncertainty of future train delays in real time. It assumes that more information continuously becomes available from the monitoring system. The dynamics of a train delay over time and space are described as a stochastic process, capturing the evolution of the time-dependent random variable. The approach is extended to model the interdependence between trains sharing the same infrastructure or having scheduled passenger transfers. The model’s application on historical traffic data from a busy corridor in Sweden demonstrates the accuracy of predictions and the evolution of probability distributions of event delays over time. This method is essential for making better predictions for train traffic, incorporating dynamic characteristics beyond static, offline-collected data (Corman & Kecman, 2018).

The objective of other study (Ulak et al., 2020) is to develop a network model and metrics that quantify the delay dependencies between transit network stops. By utilizing Bayesian network learning (at the intersection of machine learning and network science), the study identifies local sources of network-wide issues. The Bayesian network approach allows for capturing complex relationships and dependencies among several factors affecting delays. This model provides insights into the interplay between different stops within the transit network, enabling better decision-making for delay mitigation and service improvement (Ulak et al., 2020). Shoman et al. (2020)`s study proposes a deep learning-based framework for predicting bus delays at the network level. By leveraging large, heterogeneous bus transit data (GTFS) and vehicle probe data, the framework employs Bayesian networks to model the dependencies between numerous factors influencing bus delays. Bayesian networks allow for probabilistic reasoning and capture the uncertainty inherent in real-world transit systems. The framework’s application enhances reliability and optimizes travel structures in urban transit networks, providing valuable insights for transit operators and planners (Shoman et al., 2020).

Previous study (Barzal et al., 2023) investigates the use of Bayesian networks for analyzing and representing dependencies in large datasets related to train delays. By operating with graphs, Bayesian networks are suitable for understanding delays in rail networks. The article provides an overview of Bayesian network theory and recent literature on train delays. Additionally, the methods are applied to data from the Austrian railway network, demonstrating their practical applicability.

A study modelled the dynamics of bus operations using a Bayesian network framework. This approach describes the time-dependent stochastic processes of delayed evolution. The model structure captures dependencies between bus operation, passenger ridership, and road demand. By leveraging Bayesian networks, probabilistic predictions of bus delays can be made, aiding transit planning and optimization (Buchel & Corman, 2021).

Delays in Bus Rapid Transit (BRT) systems are influenced by a variety of interrelated factors, including passenger occupancy, traffic conditions, weather, operational efficiency, and infrastructure quality. When occupancy levels rise, particularly beyond 70%, there is a notable increase in the time it takes for passengers to board and alight from vehicles. This phenomenon can lead to longer delays, affecting overall transit times and service reliability (Ahac et al., 2024). Traffic congestion exacerbates these delays, especially in mixed traffic conditions; Azam et al. (2023) indicates that the use of dedicated bus lanes contributes to a reduction in bus travel times, which can be as high as 14-16% compared to conditions without such lanes (Azam et al., 2023). Additionally, studies indicate that rain can contribute to traffic congestion and delays, with rain accountable for up to 25% of total traffic delays on urban freeways (Seeherman et al., 2012). Finally, infrastructure quality, including well-maintained roads and adequate bus stops, is crucial; Huen et al. (2005) reported that infrastructure upgrades lead to a 15% decrease in delays by improving accessibility and safety (Huen et al., 2005), while Fernández, R. (2011) underscored the design of bus stops significantly contributes to reducing boarding times for passengers (Fernandez, 2011). Effective bus stop design incorporates features such as appropriate spacing, clear signage, and protective shelters, which facilitate smoother passenger flows during boarding and alighting. Addressing these factors holistically is essential for improving BRT performance and enhancing service reliability.

Bayesian networks offer a powerful approach for modeling and predicting public transportation delays, considering complex dependencies and probabilistic reasoning. These models contribute to more accurate and dynamic delay predictions, improving transit system performance. Decision trees, on the other hand, provide valuable insights into predicting public transportation delays by leveraging machine learning techniques and understanding relevant factors. By doing so, researchers can enhance transit reliability and optimize service quality.

3. METHODOLOGY

Bayes' Theorem, pioneered by Reverend Thomas Bayes, an esteemed mathematician and theologian of the 18th century, was initially disseminated in 1763 (Stutz & Cheeseman, 1994). In mathematical terms, it is articulated as follows (Niedermayer, 2008):

$$P(H \mid E, c) = \frac{P(H|c) x P(E|H,c)}{P(E|c)} \quad (1)$$

In essence, we can revise our belief in hypothesis H given supplementary evidence E and the contextual backdrop c. The expression on the left, $P(H|E,c)$, denotes the "posterior probability," signifying the probability of H subsequent to incorporating the influence of E on c. The term $P(H|c)$ denotes the "prior probability of H given c alone." $P(E|H,c)$ is termed the "likelihood," representing the probability of the evidence under the assumption that hypothesis H and the background information c hold true. Lastly, $P(E|c)$ remains uninfluenced by H and can be construed as a standardizing or scaling factor (Niedermayer, 2008). A Bayesian network characterized by its topology Ϛ (a directed acyclic graph, or DAG) and a parameter vector $\theta = \{\theta_1, \theta_2, \ldots, \theta_n\}$, encapsulates the collective probability distribution of a set of random variables $\{X_1, X_2, \ldots, X_n\}$. Employing the product rule of probability, the joint probability distribution of $X_1, X_2, \ldots, X_n$ can be expressed as (Lauría, 2008):

$$p(x|\theta, Ϛ) = \prod_{i=1}^{n} p(x_i|x_{pa(i)}, \theta_i, Ϛ) = \prod_{i=1}^{n} \theta_{ik}(j) \quad (2)$$

The notation $p(x|\theta, Ϛ)$ represents the probability of a specific combination of assignments $X_1, X_2, \ldots, X_n$ to the variables $X_i \in X$, where $x_{pa(i)}$ indicates a defined configuration of the direct parents of X_i, connected to X_i through the arcs in the DAG Ϛ. In a discrete Bayesian network, the conditional probability tables associated with each node $Xi \in X$ are characterized by parameters $\theta = \{\theta_1, \theta_2, \ldots, \theta_n\} = \{[\theta_{ik}(j)]_{k=1}^{r_i}\}_{j=1}^{q_1}$ where $i=1\ldots n$ denotes each variable $X_i \in X$, $k=1\ldots r_i$ identify each of the r_i states of variable $X_i \in X$, and $j=1\ldots q_i$ represents the q_i valid set of configurations of values of the parent variables of Xi ($x_{pa(i)}$).

In conducting the study, Genie software served as the primary tool for comprehensive network analysis and visual representations (Bayesfusion, 2024). GeNIe Modeler, an innovative graphical user interface (GUI) developed by BayesFusion, emerged as a cornerstone for constructing, refining, and analyzing Bayesian network models across diverse fields, including epidemiology, finance, and marketing. This sophisticated platform empowers researchers to visually articulate intricate relationships and dependencies within complex datasets, facilitating a deeper understanding of underlying dynamics (Bayesfusion, 2024). Moreover, GeNIe boasts extensive functionality, supporting custom functions, stochastic sampling algorithms, and diagnostic tools, thereby enhancing analytical capabilities and facilitating robust model development (Bayesfusion, 2024).

Within the framework of Bayesian network modeling, various node types play distinct roles in encapsulating decision-making processes and uncertainty. Decision nodes, typified by rectangular representations, encode variables under the control of decision-makers, thereby encapsulating available decision alternatives. These nodes, such as the "Investment Decision" node, typically offer binary choices, facilitating the delineation of decision pathways. In contrast, chance nodes, symbolized by circles or ovals, represent random variables reflecting uncertainties inherent in decision problems. Notably, the arrangement of decision nodes preceding chance nodes mirrors the conditional probability distribution of the latter, facilitating probabilistic inference.

Deterministic nodes, characterized by double-circles or double-ovals, convey either constant values or outcomes deduced algebraically from parent nodes, thereby enriching the model's predictive capacity. Conversely, value nodes, depicted as diamonds, denote utility and serve as measures of desirability for decision outcomes, quantified based on the utility associated with each possible combination of parent node outcomes.

Influence diagrams, represented by arcs, delineate relationships between nodes, with certain arcs conveying causal implications. Notably, directed paths from decision nodes to chance nodes signify decision impacts on probability distributions, illuminating causal relationships within the model. Informational arcs, directed toward decision nodes, denote temporal precedence rather than influence, signifying the flow of information and facilitating sequential decision-making processes. This interconnected network of nodes and arcs enables researchers to conduct comprehensive probabilistic analyses, elucidating causal pathways and informing decision-making processes across diverse domains.

To effectively model diverse datasets for this project, a comprehensive array of data was gathered from various sources, with surveys and reports generously provided by the Istanbul Metropolitan Municipality forming a cornerstone of this endeavor. These datasets, meticulously compiled, encompass a wide spectrum of information crucial for our analysis, covering both typical week hours and peak periods of activity. One dataset, pivotal in understanding passenger flow dynamics, delineates the number of passengers disembarking at each bus stop, denoted by specific numerical identifiers corresponding to distinct stops along the route, such as Soğütlüçeşme, Fikirtepe, and Uzunçayır.

A significant observation arose during the examination of the Söğütlüçeşme Bus Stop data, revealing a count of zero, indicative of a peculiar phenomenon where no passengers alight at this stop. Further scrutiny utilizing the Origin-Destination Matrix elucidated that all passengers embark at the initial stop, precluding any subsequent disembarkations. Our investigation focused exclusively on BRT stops situated on the Asian side of Istanbul shown in Fig. 1, motivated by the inherent variability in bus routes and the ease of data collection along the Sogutlucesme-Zincirlikuyu corridor, characterized by its compactness and accessibility.

Moreover, the dataset affords valuable insights into passenger preferences, distinguishing between those seeking shorter journeys of three stops or fewer and those opting for longer rides. Complementing these quantitative datasets are qualitative inputs garnered through face-to-face surveys, delving into demographic particulars such as age, gender, and willingness to board crowded buses. Equally pertinent is data pertaining to driver behavior, encompassing assessments of safe driving practices and the temporal dynamics governing door operations, crucial factors in ensuring passenger safety and operational efficiency. Together, this multifaceted dataset serves as the bedrock for our analytical pursuits, offering a nuanced understanding of bus transit dynamics in Istanbul's bustling urban landscape.

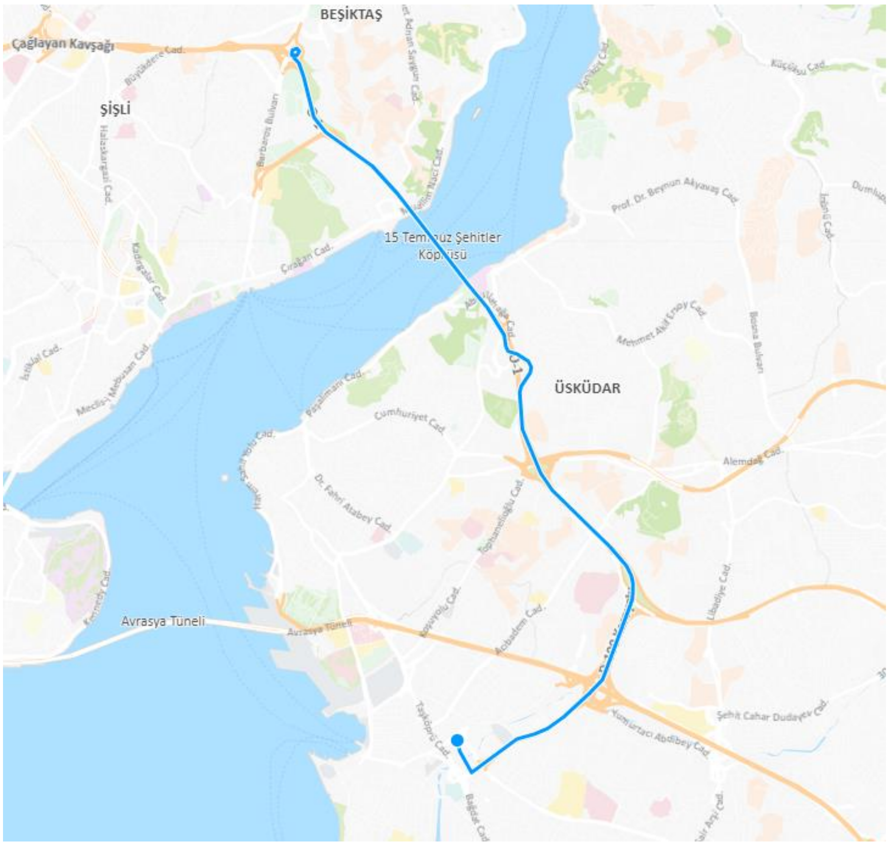

Figure 1. Asian Side Metrobüs Route

In evaluating parameters for BRT delays, several factors are considered:

1. Passenger ratio for each stop: This parameter assesses the number of passengers at each bus stop, providing insight into demand distribution along the route. Table 1 shows the passenger ratio depending on the stations. Stations are selected according to their locations and except Zincirlikuyu other stations are in Anatolian side of the Istanbul.

Table 1. Passenger ratio at the stops on the Asian side of Istanbul's BRT system

Stop	Passenger Ratio
Sogutlucesme	19%
Fikirtepe	2%
Uzuncayir	24%
Acibadem	4%
Altunizade	9%
Burhaniye	0%
Bogazici Koprusu	4%
Zincirlikuyu	38%

2. Percentage of passengers inside arriving bus: This metric indicates the degree of occupancy of buses upon arrival at stops, influencing boarding efficiency and potential delays.

Table 2. Percentage of passengers on board the arriving bus

Condition	Percentage of passengers on board the arriving bus
Full	43%
Empty	57%

3. Gender of passengers: Analyzing the gender distribution of passengers helps identify potential demographic patterns that may impact boarding and travel behaviors.

Table 3. Gender of the passengers

Gender	Percentage
Female	41%
Male	59%

4. Age of passengers: Understanding the age demographics of passengers allows for the consideration of factors such as mobility limitations or boarding speed variations.

Table 4. Age distribution of the passengers

Age Group	Percentage
15-24	28%
25-34	22%
35-44	28%
45-54	15%
Over 55	7%

5. Travel distances of passengers: Examining the distances traveled by passengers provides context for boarding and alighting behavior, which can affect overall transit times.

Table 5. Travel distance of passengers based on whether they travel fewer than or more than 3 stops.

Condition	Percentage of travel distance of passengers
Less than 3 stops	23%
More than 3 stops	77%

6. Passengers entering crowded buses: This parameter highlights situations where buses are already at or near capacity, potentially leading to delays as additional passengers attempt to board.

Table 6. Distribution of passengers who board crowded buses versus those who do not.

Condition	Percentage of passengers who board crowded buses
Entering	93%
Not Entering	7%

7. Safe driver ability: Evaluating driver performance in terms of safety practices and adherence to traffic regulations contributes to overall transit efficiency and passenger satisfaction.

Table 7. Safe driving ability

Condition	Safe driving ability
Safe	100%
Not safe	0%

8. Driver's decision time to open and close the doors: The timing and efficiency of door operations by drivers can impact dwell times at stops, affecting overall schedule adherence.

Table 8. Driver`s decision time to open and close the doors.

Reaction	Driver`s decision time to open and close the doors.
Fast	82%
Slow	18%

9. Percentage of passengers entering and exiting the bus: Analyzing the balance between passenger boarding and alighting rates provides insights into the flow dynamics within buses, influencing overall transit efficiency.

Table 9. Percentage of passengers boarding and alighting from the bus

Condition	Percentage of passengers boarding and alighting from the bus
Entering	85%
Exiting	15%

4. RESULTS

The research inquiry centers on examining the impact of various parameters on the temporal performance of BRT systems. Employing a rigorous scientific methodology, the study systematically evaluates the ramifications of parameter adjustments on system latency. Specifically, through sophisticated simulations, the study elucidates how alterations in selected parameters engender consequential shifts in system behavior. For instance, elucidating the influence of passenger occupancy on temporal delays, the investigation rigorously scrutinizes occupancy rates and their correlative effects on temporal performance.

Figure 2. illustrates the impact of various parameters on the performance of BRT systems regarding delays. At a passenger occupancy level of 43%, there is a 76% probability of no delay, highlighting how moderate occupancy significantly enhances on-time performance, although a 24% chance of delay remains. In high traffic flow conditions, the likelihood of avoiding delays drops to 55%, indicating that heavy traffic still poses a considerable risk. Weather conditions further influence performance, with clear weather yielding an 80% probability of no delays, while rainy conditions reduce this to 60%. Operational efficiency also plays a critical role; when operations are optimized, there is an 85% probability of avoiding delays, whereas non-optimized operations result in only a 50% chance of timely performance. Overall, the findings emphasize that passenger occupancy and operational efficiency are crucial for minimizing delays, while weather and traffic conditions also significantly affect system reliability. This finding underscores the intricate interplay between occupancy rates and temporal performance within the BRT system context. Furthermore, the investigation systematically explores the dynamic interrelationships between various parameters, thereby offering a comprehensive understanding of their collective impact on system temporal dynamics.

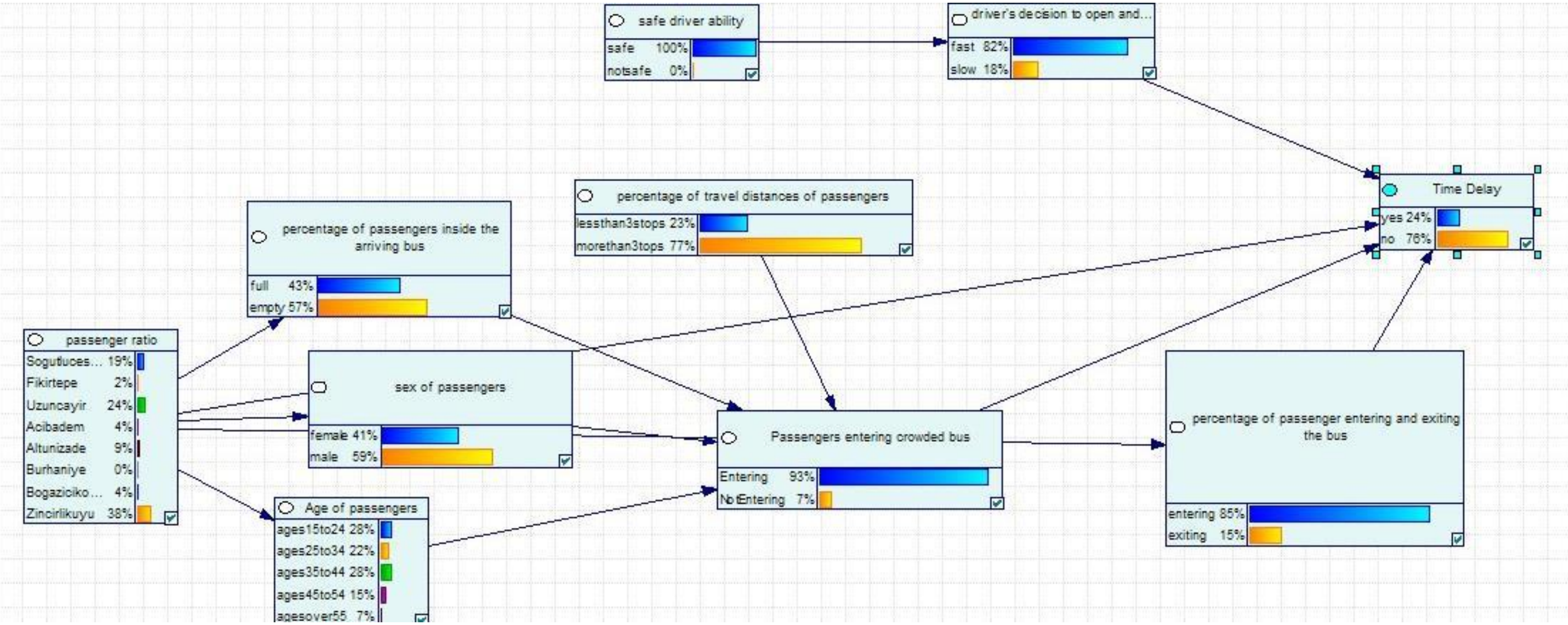

Figure 2. Decision tree for time delay under the selected conditions

Through meticulous analyses and nuanced interpretations, the study contributes valuable insights into the intricate operational dynamics of BRT systems, furnishing a solid foundation for informed decision-making and policy formulation in urban transportation planning and management. The insights from this study provide actionable guidance for Metrobus system managers to enhance operational performance. By recognizing the crucial relationships between passenger occupancy, traffic flow, and weather conditions, managers can implement strategies such as maintaining an optimal occupancy rate of around 43% to reduce delays. Additionally, integrating real-time traffic management and weather forecasting tools can help anticipate disruptions, while dynamic scheduling can further improve service reliability. Focusing on operational efficiency—through streamlined procedures, staff training, and technology investments—will also significantly decrease delay probabilities. Overall, these findings empower managers to make data-driven decisions that enhance the efficiency and reliability of the Metrobus system, contributing to a more effective urban transportation network.

Despite the valuable insights provided by this study, there are notable limitations, primarily related to data collection and availability. The analysis relied on data from diverse sources; however, the volume and granularity of data were insufficient to comprehensively explore all potential scenarios affecting BRT delays. This limitation may restrict the ability to fully capture the complexities of the Metrobus system's operational dynamics. Additionally, the lack of real-time data integration and the exploration of varying parameters could result in missed opportunities for a more nuanced analysis.

5. CONCLUSION

Traditional bus services often struggle with issues such as long waits and overcrowding, prompting the exploration of alternatives like BRT systems. While BRT systems offer advantages such as dedicated lanes and cost-effectiveness, delays within these systems can undermine their efficiency and reliability. In conclusion, this study has illuminated the significance of various parameters causes time delay in public transportation systems.

Focusing on Istanbul's Metrobus system, this study employs advanced analytical techniques including Decision Trees and Bayesian Networks to dissect the multifaceted factors influencing BRT delays. Decision Trees facilitate the identification of influential parameters, while Bayesian Networks unravel causal dependencies among variables, providing a holistic understanding of the delay dynamics. The proposed Bayesian Precedence Network integrates these methodologies with precedence relationships, offering actionable insights for optimizing BRT operations.

The study's methodology encompasses data analysis from diverse sources, including surveys and reports, coupled with the application of GeNIe Modeler for Bayesian network analysis. The results demonstrate the effectiveness of decision analysis in quantifying uncertainties and evaluating critical factors affecting BRT delays, paving the way for informed decision-making in transit planning and optimization. Notably, an occupancy rate of 43% corresponds to a 76% probability of avoiding delays, illustrating the strong relationship between passenger load and system efficiency. Additionally, the findings demonstrate that optimized operational practices can lead to an 85% probability of no delays, while adverse weather conditions and high traffic flow notably reduce this likelihood.

Moving forward, this study serves as a blueprint for future research endeavors aimed at addressing public transportation challenges. Real-time data integration and exploration of additional parameters could further enhance the predictive accuracy and applicability of decision models in optimizing transit systems. By leveraging the synergy between advanced analytics and domain expertise, transportation planners and policymakers can proactively address BRT delays, ultimately contributing to the creation of more efficient and reliable public transit networks.

This study offers several distinctive contributions compared to existing research on BRT systems. While Vuchic (2007) and Levinson et al. (2002) emphasize the importance of BRT in urban mobility and explore operational challenges, they often focus on broad descriptive factors like traffic congestion or system design. In contrast, this research adopts a novel analytical approach by integrating Decision Trees and Bayesian Networks to both identify key delay parameters and model their causal relationships. Most studies rely on regression or simulation-based models, lacking the probabilistic depth provided by Bayesian frameworks, which this study addresses by applying the Bayesian Precedence Network.

Additionally, while earlier research, highlights delays and overcrowding as critical issues, these works do not explore the interplay between factors like weather, occupancy, and driver behavior in detail. This study’s incorporation of human factors—such as driver reaction times and passengers' willingness to board crowded buses—fills an important gap in the literature by providing a more comprehensive view of delay dynamics. Furthermore, unlike general BRT studies focused on systems across multiple cities, this research offers localized insights into Istanbul's Metrobus system, examining specific stop-level variations (e.g., Söğütlüçeşme’s zero disembarkations) and corridor-specific challenges.

Future research should incorporate robust methodologies for conditional probabilities, perform comprehensive scenario and sensitivity analyses, expand data collection, integrate real-time data, assess policy impacts, and develop advanced analytical tools to enhance the understanding and efficiency of transit systems.

6. REFERENCES

Ahac, M., Majstorović, I., Ahac, S., & Bašić, S. (2024). Effect of Tram Floor Height on Passenger Boarding and Alighting Time. In *New Challenges for Sustainable Urban Mobility: Volume II* (pp. 279–288). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-62478-0_23

Azam, M., Nadeem, M., Asmah Hassan, S., & Che Puan, O. (2023). Impacts of Bus Only Lanes on Signalized Intersection Under Heterogeneous Traffic Conditions. *Suranaree Journal of Science and Technology*, *30*(1), 010185(1-11). https://doi.org/10.55766/sujst-2023-01-e01617

Barzal, V., Rößler, M., Wastian, M., Breitenecker, F., & Popper, N. (2023). Analysis of Train Delays using Bayesian Networks. *SNE Simulation Notes Europe*, *33*(2), 89–92. https://doi.org/10.11128/sne.33.sn.10645

Bayesfusion. (2024). *GeNIe Modeler*. GeNIe Modeler.

Buchel, B., & Corman, F. (2021). Probabilistic Bus Delay Predictions with Bayesian Networks. *2021 IEEE International Intelligent Transportation Systems Conference (ITSC)*, 3752–3758. https://doi.org/10.1109/ITSC48978.2021.9564537

Corman, F., & Kecman, P. (2018). Stochastic prediction of train delays in real-time using Bayesian networks. *Transportation Research Part C: Emerging Technologies*, *95*, 599–615. https://doi.org/10.1016/j.trc.2018.08.003

de Oña, J., de Oña, R., & López, G. (2016). Transit service quality analysis using cluster analysis and decision trees: a step forward to personalized marketing in public transportation. *Transportation*, *43*(5), 725–747. https://doi.org/10.1007/s11116-015-9615-0

Fernandez, R. (2011). Experimental study of bus boarding and alighting times. *European Transport Conference*, 1–14.

Halyal, S., Mulangi, R. H., Harsha, M. M., & Laddha, H. (2022). *Study on Travel Time Characteristics of Hubli-Dharwad Bus Rapid Transit System in Comparison with Heterogeneous Traffic Lane* (pp. 701–712). https://doi.org/10.1007/978-981-16-4396-5_61

Huen, K., Tighe, S., & McCabe, B. (2005). Incorporating User Delay Cost in Project Selection: A Canadian Case Study. *1st Annual Inter-University Symposium on Infrastructure Management*, 1–21.

Istanbul Metropolitan Municipality. (2023). *Istanbul Metropolitan Municipality*. Https://Www.Ibb.Istanbul/En.

Jayakumar, M., & Maji, A. (2023). Decision Tree Analyses of Safety and Comfort Perceptions for Public Transportation in Kalyan-Dombivli Region of Maharashtra. *Transportation in Developing Economies*, *9*(2), 14. https://doi.org/10.1007/s40890-023-00184-9

Kavalov, R. (2019, October 25). *Predicting NJ Transit Delays Using Decision Trees*. Medium.

Koller, D., & Friedman, N. (2009). *Probabilistic Graphical Models: Principles and Techniques Adaptive Computation and Machine Learning series*. MIT Press.

Lauría, E. J. M. (2008). An Information-Geometric Approach to Learning Bayesian Network Topologies from Data. In *Innovations in Bayesian Networks* (pp. 187–217). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-85066-3_8

Levinson, H., Zimmerman, S., Clinger, J., & Rutherford, G. (2002). Bus Rapid Transit: An Overview. *Journal of Public Transportation*, *5*(2), 1–30. https://doi.org/10.5038/2375-0901.5.2.1

Niedermayer, D. (2008). An Introduction to Bayesian Networks and Their Contemporary Applications. In *Innovations in Bayesian Networks* (pp. 117–130). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-85066-3_5

Seeherman, J., Sisiopiku, V. P., & Skabardonis, A. (2012). Assessment of the Impact of Weather on Freeway Operations in California. *Proceedings of the 91st Transportation Research Board Annual Meeting*.

Shoman, M., Aboah, A., & Adu-Gyamfi, Y. (2020). Deep Learning Framework for Predicting Bus Delays on Multiple Routes Using Heterogenous Datasets. *Journal of Big Data Analytics in Transportation*, *2*(3), 275–290. https://doi.org/10.1007/s42421-020-00031-y

Stutz, J., & Cheeseman, P. (1994). *A Short Exposition on Bayesian Inference and Probability. National Aeronautic and Space Administration Ames Research Centre: Computational Sciences Division*.

Ulak, M. B., Yazici, A., & Zhang, Y. (2020). Analyzing network-wide patterns of rail transit delays using Bayesian network learning. *Transportation Research Part C: Emerging Technologies*, *119*, 102749. https://doi.org/10.1016/j.trc.2020.102749

Vuchic, V. R. (2007). *Urban Transit Systems and Technology*. Wiley. https://doi.org/10.1002/9780470168066

Wang, J., Han, Y., & Li, P. (2022). Integrated Robust Optimization of Scheduling and Signal Timing for Bus Rapid Transit. *Sustainability*, *14*(24), 16922. https://doi.org/10.3390/su142416922

Wu, W., Luo, X., & Shi, B. (2023). Offset Optimization Model for Signalized Intersections Considering the Optimal Location Planning of Bus Stops. *Systems*, *11*(7), 366. https://doi.org/10.3390/systems11070366

Xu, Q., Liu, S., & Li, Z. (2013). Bayesian Network Models for Transportation Planning. *Springer Science & Business Media*.