Khandagale Pratiksha Mangesh2026, 14:5
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

Smart Bus Tracking And Monitoring System: A Review Of Gps–Iot Vehicle Tracking, Arrival-Time Prediction And Passenger Information Services

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Abstract—Public bus services carry large numbers of passengers in Indian cities, yet passengers often wait at stops without knowing when the next bus will arrive, and operators lack real-time visibility of their fleets. A smart bus tracking and monitoring system uses GPS, IoT communication and web or mobile applications to provide live bus locations, routes, estimated arrival times and schedules to passengers and transport authorities. This paper reviews the technologies behind such systems. It covers GPS-based vehicle tracking, onboard IoT units with cellular communication, trajectory processing and map matching, and methods for predicting bus arrival times, from historical averages and Kalman filtering to artificial neural networks and recurrent models that account for traffic and multiple routes. Smartphone-based crowdsourced tracking and research on the effect of real-time information on passengers are reviewed, together with open data standards. A five-layer architecture comprising onboard units, communication, a central server with prediction, administrator tools and passenger applications is proposed. Research gaps, objectives, a comparison of prediction methods and challenges including GPS errors in dense areas, data costs and privacy are discussed. The review concludes that integrating AI-based prediction makes bus services more reliable and attractive.

Index Terms—Smart bus tracking, GPS, IoT, arrival time prediction, public transport, intelligent transportation systems, Kalman filter, neural networks

I. INTRODUCTION

Buses are the backbone of public transport in many Indian cities, but uncertainty about arrival times discourages their use. Passengers may wait for long periods or give up and choose private vehicles, adding to congestion and pollution. Operators, meanwhile, often rely on manual logs to monitor punctuality and driver behaviour.

GPS receivers and cellular IoT modules now allow every bus to report its location continuously. When combined with software that predicts arrival times, this data can be shared with passengers through apps and display boards. Ferris *et al.* [1] showed with OneBusAway that real-time arrival information increased passenger satisfaction and reduced perceived waiting time.

This paper reviews the components of a smart bus tracking and monitoring system and the AI methods that improve its predictions, and proposes an architecture.

II. BACKGROUND AND FUNDAMENTAL CONCEPTS

1. System Components

Fig. 1 summarizes the main functions: live tracking, arrival prediction, passenger information, fleet monitoring and analytics.

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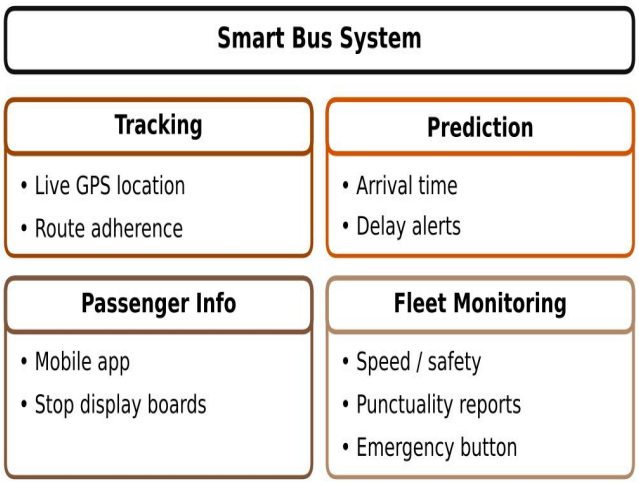


Fig. 1. Functions of a smart bus tracking and monitoring system.

2. Location Data Processing

GPS readings contain noise and gaps. Map matching aligns readings to the road network, and trajectory data mining techniques [2] extract speeds, dwell times and travel times between stops.

III. LITERATURE SURVEY

Chien *et al.* [3] used artificial neural networks to predict dynamic bus arrival times from link and stop characteristics and found them more accurate than simple models. Jeong and Rilett [4] compared historical averages, regression and neural networks and found neural networks best for arrival prediction in congested traffic.

Yu *et al.* [5] predicted arrival times at stops served by multiple routes, using running times of other routes' buses on shared segments to improve accuracy. Kalman filtering [6] has been widely used to update arrival predictions as new GPS positions arrive.

Biagioni *et al.* [7] presented EasyTracker, which uses smartphones on buses to track vehicles, infer routes and stops and predict arrivals without dedicated hardware, a low-cost option for smaller cities. Thiagarajan *et al.* [8] developed VTrack to estimate road delays from phone location data in an energy-efficient way.

Ferris *et al.* [1] evaluated the effect of real-time information on riders, and the GTFS Realtime specification [9] defined a standard format for sharing live vehicle positions and predictions with third-party apps. Recurrent networks such as LSTM [10] are now used to capture temporal traffic patterns in travel-time prediction. Table I summarizes these works.

Ref.	Authors	Year	Technique Used	Merits	Demerits
[6]	Kalman	1960	Kalman filter	Optimal recursive estimation	Linear assumptions
[3]	Chien et al.	2002	ANN for dynamic arrival prediction	More accurate than simple models	Simulated data
[4]	Jeong and Rilett	2004	Historical vs. regression vs. ANN	ANN best in congestion	Single route
[8]	Thiagarajan et al.	2009	VTrack delay estimation	Energy-aware phone tracking	Cars, not buses
[1]	Ferris et al.	2010	OneBusAway evaluation	Real-time info improves satisfaction	Single city
[5]	Yu et al.	2011	Multi-route stop prediction	Uses shared-segment information	Needs dense data

Ref.	Authors	Year	Technique Used	Merits	Demerits
[7]	Biagioni et al.	2011	EasyTracker with smartphones	Low-cost automatic tracking	Phone reliability
[2]	Zheng	2015	Trajectory data mining overview	Map matching and travel-time extraction	General, not bus-specific

TABLE I Summary of Literature Survey

IV. RESEARCH GAP

- **G1:** Arrival predictions degrade in heavy, unpredictable traffic common in Indian cities.
- **G2:** GPS accuracy suffers in dense urban areas, flyovers and narrow streets.
- **G3:** Many systems are not integrated with open data standards, limiting app access.
- **G4:** Passenger crowding information is rarely provided.
- **G5:** Data on driver behaviour and safety is under-used.

V. OBJECTIVES

- 1. To review GPS–IoT tracking technologies for buses.
- 2. To examine arrival-time prediction methods from statistical to deep learning.
- 3. To propose a five-layer smart bus tracking and monitoring architecture.
- 4. To compare prediction methods.
- 5. To identify challenges and future enhancements, including AI-based route optimization.

VI. PROPOSED SYSTEM ARCHITECTURE

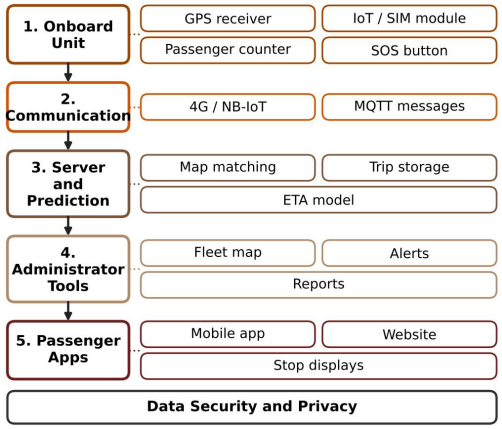


Fig. 2 shows the proposed architecture.

Fig. 2. Proposed five-layer smart bus tracking and monitoring architecture.

1. Onboard Unit Layer

Each bus has a GPS receiver, an IoT module with a SIM card, optional passenger counters and an emergency button.

2. Communication Layer

The unit sends location, speed and status every few seconds over 4G or NB-IoT using lightweight protocols such as MQTT [11].

3. Central Server And Prediction Layer

The server map-matches positions, stores trips and predicts arrival times at upcoming stops using a model that combines historical patterns with live speeds.

4. Administrator Layer

Operators monitor buses on a map, receive alerts for delays, route deviations, over-speeding or emergencies and analyse punctuality reports.

5. Passenger Application Layer

Passengers see live bus positions, predicted arrival times and service alerts in a mobile app, on a website and on display boards at stops.

VII. METHODOLOGY AND WORKING

Fig. 3 shows the workflow. Predicted arrival time at stop s is the current time plus the sum of predicted travel times for remaining segments and dwell times:

$$ETA_s = t_{now} + \Sigma (\hat{T}_{segment} + \hat{D}_{stop}) \quad (1)$$

where segment times are predicted by the model. A Kalman filter updates the estimate $\hat{x}$ as each new GPS measurement z arrives:

$$\hat{x}_k = \hat{x}_k^- + K_k (z_k - H \hat{x}_k^-) \quad (2)$$

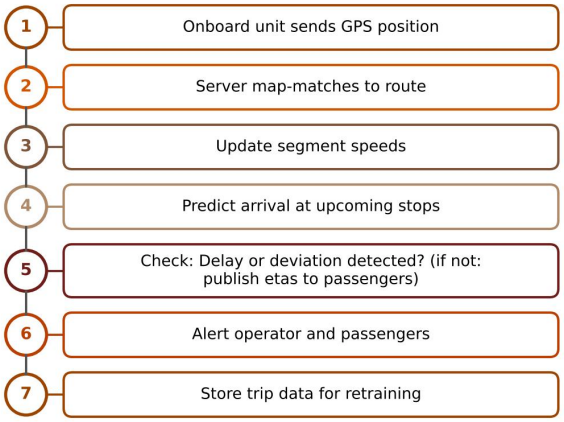


Fig. 3. Bus tracking and arrival prediction workflow.

Prediction accuracy is measured with mean absolute error in minutes, reported separately for peak and off-peak periods.

VIII. COMPARATIVE ANALYSIS

Table II compares prediction methods. Historical averages are simple but ignore live conditions, Kalman filters adapt smoothly, neural networks capture non-linear effects and LSTMs model temporal traffic patterns best.

Method	Accuracy	Live Data	Complexity
Historical average	Low	No	Very low
Regression	Medium	Partly	Low
Kalman filter	Medium–High	Yes	Low
Neural network	High	Yes	Medium
LSTM	Very high	Yes	High

TABLE II Comparison of Arrival-Time Prediction Methods

IX. CHALLENGES AND FUTURE SCOPE

Table III summarizes challenges. Future enhancements include AI-based route and schedule optimization, crowding prediction, integration with metro and other modes for journey planning and digital ticketing linked to tracking data.

Challenge	Mitigation
GPS errors	Map matching; filtering
Unpredictable traffic	Live-speed models; LSTM
Data costs	Adaptive reporting intervals
Passenger privacy	No personal tracking; aggregate data
Interoperability	GTFS / GTFS-RT standards

TABLE III Challenges and Mitigation

X. CONCLUSION

A smart bus tracking and monitoring system gives passengers reliable information and operators real-time control of their fleets. The reviewed literature shows that GPS–IoT tracking is mature and that arrival prediction improves significantly with Kalman filtering and neural networks. By adopting open data standards and AI-based prediction, cities can reduce waiting times, improve punctuality and make public transport more attractive.

1. Acknowledgment

The authors express their sincere gratitude to the Department of Artificial Intelligence and Data Science, Jaihind College of Engineering, Pune, for providing the facilities, guidance and encouragement needed to carry out this work. The authors also thank the faculty members and colleagues whose valuable suggestions helped improve the quality of this review.

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