

Traffic Control System Using Zigbee Powered IoT and Automated Divider Mechanism for Smart City Applications

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Abstract

The rapid growth of urbanization and vehicular density has significantly increased traffic congestion worldwide, with over 1.4 billion vehicles on roads and urban traffic delays causing nearly 20–30% productivity loss in major cities, while smart traffic management systems are expected to grow at over 18% annually. Additionally, inefficient lane utilization during peak hours leads to severe congestion, fuel wastage, and increased carbon emissions, highlighting the need for adaptive infrastructure solutions. Traditional traffic management systems rely on static dividers and fixed lane allocations, which fail to adapt to fluctuating traffic conditions, resulting in inefficient road usage, increased delays, and higher accident risks. Moreover, manual traffic control methods are labour-intensive, less responsive, and lack real-time data-driven decision-making capabilities. To overcome these challenges, the proposed IoT-enabled automated moving divider system utilizes ZigBee wireless communication to create a smart and adaptive traffic management solution. The system integrates distributed sensor networks to monitor vehicle density and traffic flow, transmitting real-time data to a central processing unit for analysis. Based on traffic conditions, motorized divider mechanisms dynamically adjust lane allocation by shifting laterally, optimizing road space utilization. ZigBee ensures low-power, reliable communication between sensors and actuators, while IoT integration enables remote monitoring, data logging, and predictive analytics for future traffic planning. This intelligent system enhances traffic efficiency, reduces congestion and fuel consumption, and supports the development of sustainable and smart urban transportation infrastructures.

Keywords: Dynamic Lane Allocation, Internet of Things, Motorized Divider System, Smart City Infrastructure, Traffic Flow Optimization, Wireless Sensor Networks, ZigBee Communication

1. Introduction

The rapid growth of urbanization and vehicular population has significantly increased the burden on existing transportation infrastructure, leading to severe traffic congestion worldwide [1]. Recent studies indicate that global urban traffic congestion results in billions of hours of lost productivity annually, while the number of vehicles on roads is expected to exceed 2 billion by 2035 [2]. Additionally, inefficient traffic management contributes to increased fuel consumption, higher carbon emissions, and economic losses. With the emergence of smart city initiatives and intelligent transportation systems, there is a growing demand for adaptive traffic control solutions capable of responding

to real-time traffic conditions [3]. Technologies such as IoT and wireless communication are playing a crucial role in enabling dynamic and efficient traffic management systems.

Problem Statement: Traditional traffic management systems rely on static road infrastructure, fixed lane divisions, and pre-programmed traffic signals that do not adapt to real-time variations in traffic flow. Road dividers are permanently installed, providing equal lane distribution regardless of traffic demand in either direction [4]. These systems are often unable to handle asymmetric traffic conditions, such as peak-hour congestion where one side of the road experiences significantly higher traffic density than the other. Moreover,

conventional methods depend heavily on manual intervention by traffic personnel, which is time-consuming, less efficient, and prone to human error [5]. The lack of real-time communication and coordination further limits the effectiveness of these systems in modern urban environments.

Research Motivation: In real-time scenarios, these limitations lead to several critical challenges affecting traffic efficiency and commuter experience. Fixed lane allocation results in underutilization of road space on one side and severe congestion on the other, especially during rush hours. This imbalance increases travel time, fuel consumption, and environmental pollution [6]. Additionally, the absence of adaptive control systems prevents timely response to sudden traffic surges, accidents, or roadblocks. Manual traffic control methods are often inadequate to handle dynamic conditions, leading to delays and inefficiencies. These challenges highlight the need for an intelligent, IoT-based solution that can dynamically adjust road infrastructure, optimize lane utilization, and ensure smooth traffic flow through real-time monitoring and automated decision-making.

2. Literature Survey

Wang et al. [7] proposed a reinforcement learning-based approach for automated lane change maneuvers that enabled vehicles to learn optimal policies through interaction with dynamic traffic environments. Mirchevska et al. [8] proposed a high-level decision-making framework for autonomous lane changing using reinforcement learning that ensured safety and rational behavior in complex traffic scenarios. Chen et al. [9] proposed a deep multi-agent reinforcement learning framework for highway on-ramp merging in mixed traffic environments.

Foerster et al. [10] proposed a counterfactual multi-agent policy gradient method that improved learning efficiency in multi-agent reinforcement learning environments. Desjardins et al. [11] proposed a cooperative adaptive cruise control system using

reinforcement learning that enabled vehicles to maintain safe distances and coordinated speeds. Chen et al. [12] proposed a multi-agent reinforcement learning-based decision-making system for cooperative driving of twin vehicles in stochastic highway environments.

Santini et al. [13] proposed a distributed and consensus-based approach for platooning maneuvers in vehicular networks that enabled coordinated vehicle movement through communication and agreement protocols. Fabiani et al. [14] proposed a generalized mixed-integer potential game framework for multi-vehicle automated driving that modeled interactions among vehicles as strategic decision-making problems.

Ye et al. [15] proposed an automated lane change policy using proximal policy optimization-based deep reinforcement learning that improved stability and performance of learned driving policies. Hu et al. [16] proposed a rear anti-collision decision-making methodology based on deep reinforcement learning for autonomous commercial vehicles. Tang et al. [17] proposed a highway decision-making and motion planning framework using soft actor-critic reinforcement learning algorithms.

Kamran et al. [18] proposed a distributional reinforcement learning-based method to minimize safety interference while ensuring comfortable automated driving. Jafari et al. [19] proposed an integrated logic and reinforcement learning framework for hybrid decision-making in autonomous vehicle planning.

3. Proposed System

The proposed IoT-enabled automated moving divider system as shown in Figure 1 introduces a revolutionary approach to traffic management by implementing a physically reconfigurable road infrastructure that dynamically adjusts lane allocation based on real-time traffic conditions using ZigBee wireless communication technology. The system integrates ultrasonic sensors, infrared sensors, or inductive loop detectors positioned on both

sides of the roadway to continuously measure traffic density, vehicle speed, and queue length, with data transmitted wirelessly via ZigBee modules to a centralized or distributed edge computing control unit.

Upon detecting traffic imbalance, the control unit sends commands through the ZigBee network to actuate motorized mechanisms—such as linear actuators, servo motors, or hydraulic systems—embedded in the movable divider structure, causing it to shift laterally and reallocate road width to favor the congested direction. The system features fail-safe mechanisms including emergency stop protocols, obstacle detection to prevent accidents during divider movement, visual warning signals (LED indicators and electronic signboards) to alert drivers of lane changes, and backup power systems to ensure operation during outages.

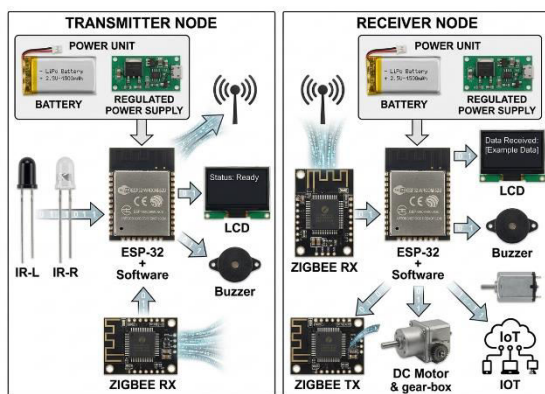


Figure 1. Proposed System Architecture.

The IoT framework enables cloud connectivity for historical data analysis, pattern recognition for predictive traffic management, remote monitoring and control via mobile applications or web dashboards, and seamless integration with existing smart city infrastructure including traffic signals, navigation apps, and emergency vehicle routing systems.

This proposed solution offers significant advantages including real-time adaptability without human intervention, optimized road capacity utilization, reduced congestion and travel time, lower fuel consumption and emissions, cost-effectiveness compared to road

expansion projects, scalability for implementation on highways and urban arterial roads, and data-driven insights for long-term urban planning and infrastructure development.

3.1 Working Procedure

The IoT-enabled automated moving divider system consists of two interconnected modules that communicate wirelessly via ZigBee technology to enable dynamic traffic flow management. Figure 2 represents the Transmitter Module (Sensing Unit) deployed at the roadside, where two environmental sensors—EV-L (left side sensor) and EV-R (right side sensor)—continuously monitor traffic density on both directions of the road by detecting vehicle presence, count, and congestion levels using ultrasonic, infrared, or inductive sensing technologies.

These sensors feed real-time traffic data to an ESP-32 microcontroller, a powerful IoT-enabled processor with built-in Wi-Fi and Bluetooth capabilities, which runs embedded software to process sensor inputs, compare traffic conditions between left and right lanes, and make intelligent decisions about lane allocation requirements. The entire transmitter module is powered by a battery backup system to ensure uninterrupted operation during power outages, and upon detecting traffic imbalance, the ESP-32 transmits control commands wirelessly through the ZigBee TX (transmitter) module using the low-power ZigBee communication protocol, which offers reliable mesh networking capabilities ideal for outdoor traffic infrastructure applications.

The Receiver Module (Actuation Unit) installed at the movable divider mechanism, where a ZigBee RX (receiver) module receives the wireless commands transmitted from the sensing unit and forwards them to another ESP-32 microcontroller running control software that interprets the instructions and coordinates the physical response.

This receiving ESP-32 is powered by a regulated power supply that converts mains AC voltage or battery power to stable DC voltage

required by the electronic components, and it controls three output devices: an LCD display that shows system status, current traffic conditions, and operational messages for maintenance personnel or drivers; a buzzer that provides audible alerts and warnings when the divider is about to move, ensuring safety by

notifying nearby vehicles and pedestrians; and a motor (likely a stepper motor, servo motor, or DC motor with gear mechanism) that physically actuates the movable divider structure, causing it to shift laterally along guide rails to reallocate lane width based on traffic demands.

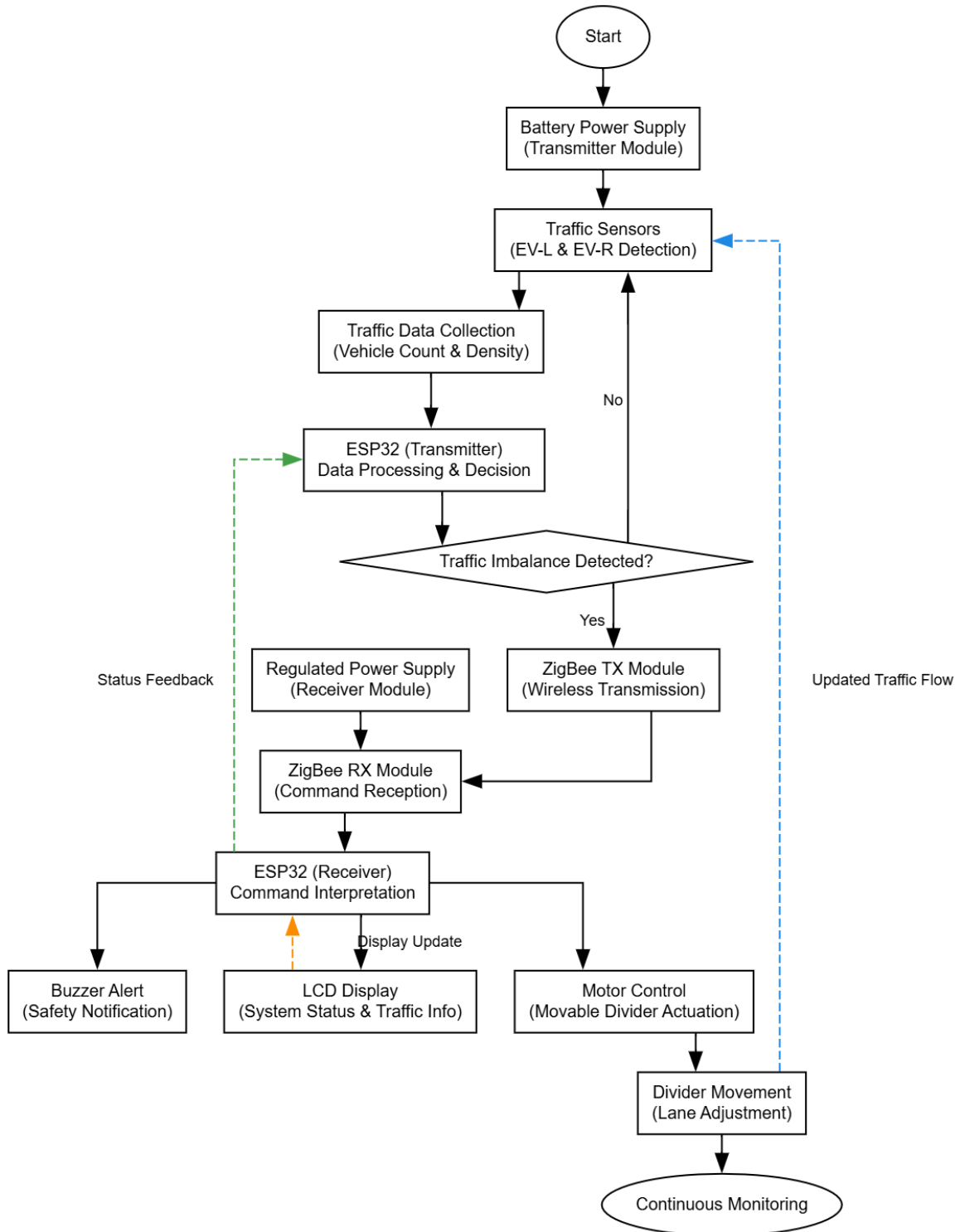


Figure 2. Proposed System Working Procedure.

4. Results and Discussion

Figure 3 shows the transmitter unit of the IoT-based automated traffic divider system. It consists of an ESP32 microcontroller, ZigBee communication module, power supply unit, LCD display, and buzzer used for monitoring traffic conditions and transmitting control signals wirelessly.

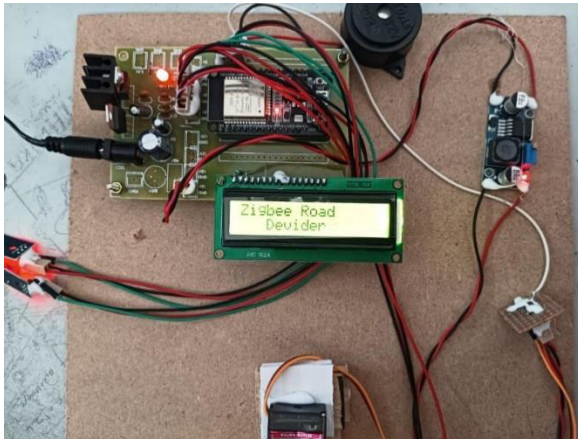


Figure 3. ZigBee Road Divider Transmitter Unit

Figure 4 shows the automated road divider mechanism in the center position. The LCD display indicates the system status while the servo motor mechanism maintains the divider at the middle position when traffic density on both sides of the road is balanced.

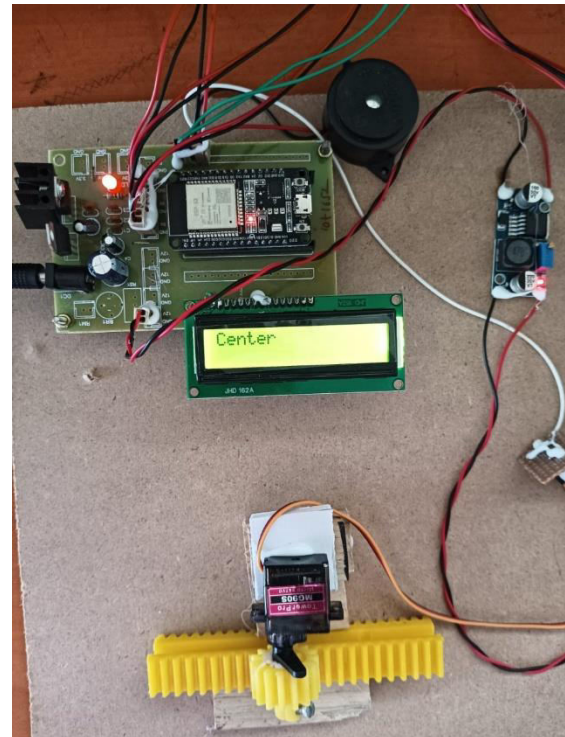


Figure 4. Centre Position of the Automated Divider

Figure 5 illustrates the operation of the automated divider when traffic flow is heavier on one side. The LCD display shows "Left", indicating that the divider is shifting towards the left side using a servo motor mechanism to allocate more road space to the opposite traffic lane.

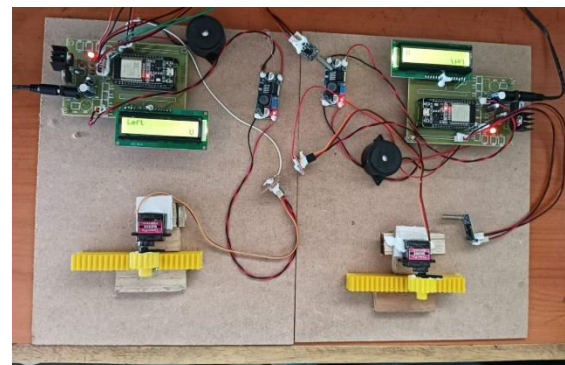


Figure 5. Divider Moving Towards Left Side Based on Traffic Condition

Figure 6 shows the operation of the automated road divider when traffic density is higher on the opposite lane. The LCD display indicates "Right", showing that the system has detected higher traffic flow and the divider is shifting towards the right side using the servo motor mechanism to dynamically allocate more road space.

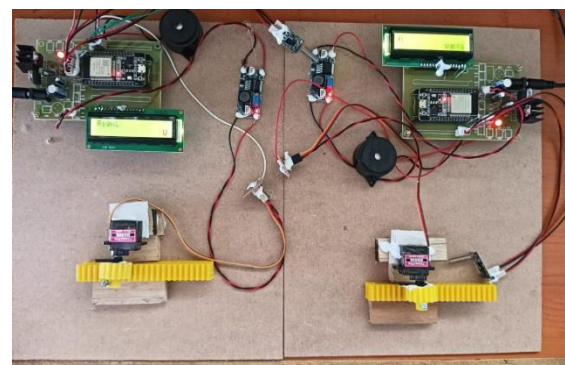


Figure 6. Divider Moving Towards Right Side Based on Traffic Condition

5. Conclusion

The proposed IoT-enabled automated moving divider system presents an innovative and efficient approach to modern traffic management by enabling dynamic lane allocation based on real-time traffic conditions. By integrating ZigBee-based wireless communication with distributed sensors and motorized divider mechanisms, the system effectively monitors vehicle density and optimizes road space utilization. This adaptive functionality overcomes the limitations of traditional static dividers, reducing congestion, travel delays, and fuel consumption while enhancing overall traffic flow and safety. Additionally, IoT-based remote monitoring and data analytics support informed decision-making and future traffic planning. By minimizing manual intervention and enabling responsive, data-driven control, the system contributes to the development of smart, sustainable, and efficient urban transportation infrastructure, addressing the growing challenges of urbanization and vehicular expansion.

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