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RFID-Based Automatic Headlight Switching with Cloud Telemetry and AI Traffic Analytics: An IoT Framework for Glare-Free Night Driving

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Abstract

Glare from a high beam left on at night is a real hazard on highways, mainly because drivers forget to dip their lights, or do it too late, when another vehicle comes into view. Automatic dipping systems built on cameras, LiDAR or radar work well but cost too much for most vehicles, and the cheap light-sensor circuits only respond to light that has already reached the car. This paper describes a design, backed by a literature survey, for an automatic headlight controller that uses the road itself as the signal source. Passive RFID tags are fixed at the beginning and end of a zone. An RC522 reader (13.56 MHz) on the vehicle sends each tag identifier to an Arduino UNO, which looks it up in a rule table and moves the headlight between low and high beam with no action from the driver. We also built a software platform around the controller: a Python bridge, Google Firebase Realtime Database, an analytics engine that fits a line to the hourly entry counts and uses *K*-means to sort the hours into off-peak, normal and rush-hour groups, and a web dashboard. We looked at twenty studies from 2021 to 2026, and none of them uses RFID tags to change a vehicle's beam. The paper lists seven research gaps, explains the pipeline and its fail-safe switching rule, and compares the idea with existing methods. We demonstrated the analytics on synthetic traffic data. Hardware measurements and field evaluation are planned for later stages.

Keywords: RFID, Internet of Things, automatic headlight control, glare reduction, Arduino, Firebase, traffic forecasting, *K*-means, road safety

Introduction

On a highway the high beam helps the driver see as far as possible along the road, but it also makes it hard for people coming the other way to see clearly. Being dazzled can blind a driver for a moment, and that moment is enough to cause a crash. Responsibility for dipping the lights currently sits with the driver, and in practice many forget or act late.

Automated options already exist. Adaptive driving beam (ADB) units spot oncoming vehicles with a camera, LiDAR or radar and then shape the light pattern around them [5], [17]. They perform well, yet they are expensive and are found mostly on premium cars. Cheaper designs based on light-dependent

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resistors (LDR) and ultrasonic sensors [6], [18] take the driver out of the loop, but they can only respond to light that has already arrived at the vehicle.

Meanwhile, radio-frequency identification (RFID) and the Internet of Things (IoT) are turning roads into connected infrastructure. RFID is common for identifying and locating vehicles and for traffic management [11]–[13], [16], but we found little evidence of it being used to control a vehicle's own lamps. We therefore propose a headlight controller in which tags placed at the start and end of a zone tell the vehicle when to change beam, and a cloud-connected software layer logs each crossing and turns the records into traffic analytics (Fig. 1).

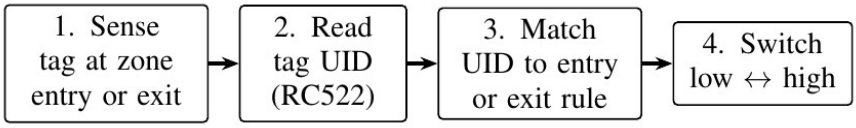


Fig. 1. The four stages of the proposed RFID headlight controller.

The problem addressed is simple: drivers often fail to lower their lights in time, which creates glare, and there is no easily retrofitted system that automatically shifts the beam using road data. The contributions are a survey of twenty studies (2021–2026) with seven research gaps; a four-stage RFID-to-beam pipeline on an Arduino UNO and an RC522 reader with a fail-safe switching algorithm; a cloud software platform with AI traffic analytics demonstrated on synthetic data; and a read-window model, a security analysis and a planned test method.

RFID Background

A passive tag has no battery. At 13.56 MHz the field of the reader induces a voltage in the coil of the tag through inductive coupling, and that voltage powers the tag chip. The tag answers by load modulation, and the reader notices the small disturbance in its field. Since a tag needs no power supply, one fixed at a zone boundary needs neither wiring nor maintenance power. HF readers such as the RC522 are inexpensive and good enough for a first prototype of the control logic, whereas UHF suits highway speeds better.

The RC522 board is based on the MFRC522 chip, which handles ISO/IEC 14443 A tags and talks to the host over SPI at 3.3 V. After every successful read it returns the unique identifier (UID) of the tag; our firmware accepts four-byte UIDs only. The chip is meant for short range, typically a few centimetres, and this shapes the deployment discussion later on. Some cheap cards also let the UID be overwritten, so a UID alone is not enough for a safety function.

Literature Survey

We reviewed twenty papers published between 2021 and 2026 and sorted them into sensor-based (5), camera and adaptive driving beam (5), AI-based (4) and RFID and IoT (6) work (Table 1).

Sensor-based control. Toney and Bhargava [17] and Nkrumah *et al.* [5] review adaptive headlamps and beam-intensity control; neither builds a controller. Mahadevan and Gurusamy [18] and Sumithra *et al.* [6] built cheap LDR-based switching, but these rely on the local light level and have trouble separating

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vehicles from street lamps. Nkrumah *et al.* [7] added radar and reported a 98% success rate in simulation, yet the LDR remains short-ranged and weather sensitive.

Camera and ADB systems. Deng *et al.* [19], Radoš *et al.* [20], Giang and Dinh [21], Li *et al.* [15] and Zhang *et al.* [9] control the beam from the angle of the oncoming vehicle, multi-sensor light management or pixel shading of an LED matrix. All of these need onboard vehicle detection, a camera and usually matrix LED lamps, and none takes input from the road infrastructure.

AI-based methods. Somasiri *et al.* [10] and Maheswari *et al.* [8] use deep-learning detection and a Raspberry Pi with a convolutional neural network. A 2025 preprint [4], not peer reviewed, combines YOLOv8, LiDAR and vehicle-to-vehicle exchange. Patil *et al.* [2] report 99.3% beam-switching accuracy and latency below 60 ms, but only in simulation and hardware-in-the-loop with GPU-class hardware.

RFID and IoT methods. Chen *et al.* [16] locate vehicles with UHF-RFID where GPS fails, and a further study [11] tracks tags for vehicle identification at high speed. An Arduino UNO design [12] reads road-embedded tags over about 30 cm but only drives an LCD. Manjunatha *et al.* [13], Hidayat *et al.* [14] and Deshkar *et al.* [3] address signal priority and street lights. None of these controls the headlights of a vehicle.

Table 1. Summary of Reviewed Literature (Latest First)

Ref.	Year	Category	Method	Main limitation
[2]	2026	AI	Hybrid PLC and YOLOv8n	Simulation/HIL only
[3]	2026	RFID/IoT	Arduino Mega, RFID, solar	Infrastructure side only
[4]	2025	AI	YOLOv8, LiDAR, V2V	Preprint; needs V2V units
[5]	2024	Sensor (review)	Beam-intensity control	No controller tested
[6]	2024	Sensor	LDR, transistor, relay	Confuses street lamps
[7]	2024	Sensor	Arduino, LDR, radar	Short range, weather
[8]	2024	AI	Raspberry Pi with CNN	Needs camera
[9]	2023	Camera/ADB	ADB with lamp control	Camera view and lighting
[10]	2023	AI	Deep-learning detection	Camera- and compute-heavy
[11]	2023	RFID/IoT	RF tag tracking, vehicle ID	No actuation
[12]	2023	RFID/IoT	UNO with UHF reader	About 30 cm; LCD only
[13]	2023	RFID/IoT	RFID, IR, weight sensors	Signals, not headlights

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Ref.	Year	Category	Method	Main limitation
[14]	2023	RFID/IoT	Arduino IoT street lights	No vehicle ID
[15]	2022	Camera/ADB	Multi-vehicle pixel shading	Needs matrix LEDs
[16]	2022	RFID/IoT	UHF-RFID localisation	No lighting control
[20]	2021	Camera/ADB	AUTOSAR light management	No infrastructure input
[17]	2021	Sensor (review)	Adaptive headlamp models	No infrastructure control
[18]	2021	Sensor	Arduino, LDR, ultrasonic	Short range
[19]	2021	Camera/ADB	Oncoming-vehicle angle	Onboard detection only
[21]	2021	Camera/ADB	LED-matrix, image processing	Needs matrix headlamps

Research Gaps

We identified seven research gaps: (1) *manual dependence*, as beam changes still rely on the driver acting in time; (2) *costly perception*, since camera, LiDAR and radar systems need expensive hardware; (3) *local sensing only*, as LDR and camera methods see only light already ahead of the car; (4) *no infrastructure link*, since road context is seldom used to trigger a beam change; (5) *weather sensitivity*, as optical sensors perform worse in fog, rain and oncoming glare; (6) *simulation-only tests*, since many designs were validated only in simulation or in the laboratory; and (7) *hard to retrofit*, as advanced systems are difficult to fit to low-end vehicles. Table 2 relates each gap to the method families. Among the studies we reviewed, none uses roadside RFID tags to switch headlight beams at low cost, and this is the space the proposed system is meant to occupy.

Table 2. Research Gaps Versus Method Families (Qualitative)

Gap	LDR	Camera	AI	RFID	Proposed
1 Manual dependence	Yes	Yes	Yes	No	Yes
2 Costly perception	Yes	No	No	Yes	Yes
3 Local sensing only	No	No	No	Yes	Yes
4 Infrastructure link	No	No	No	Partly	Yes

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Gap	LDR	Camera	AI	RFID	Proposed
5 Weather sensitivity	No	No	Partly	Yes	Yes
6 Simulation-only tests	Partly	Partly	No	Partly	Partly
7 Hard to retrofit	Yes	No	No	Partly	Yes

Yes = addressed, Partly = partly addressed, No = not addressed; RFID = RFID in ITS. Judged from the characteristics reported in the reviewed papers; the last column is design intent to be verified.

Proposed System

A. Overview and Hardware

Passive tags sit at the entry and exit points of a road zone (Fig. 2). When a vehicle passes a tag, the on-board RC522 reader reads the UID of the tag and sends it to an Arduino UNO, which checks the UID against stored entry and exit identifiers and drives the headlight output. An entry tag marks a busy or lit zone and selects low beam, while an exit tag marks an open dark stretch and selects high beam. The beam is therefore chosen from road context before any optical sensor has had to detect an oncoming vehicle.

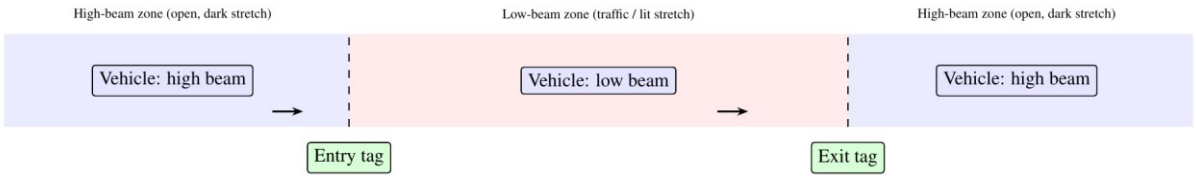


Fig. 2. Deployment scenario. Entry and exit tags at the boundaries of a low-beam zone make the on-board controller change beam as the vehicle passes each one.

The prototype connects the RC522 to the UNO over SPI (D10 SS, D13 SCK, D11 MOSI, D12 MISO, D9 RST) and drives two outputs: LED1 on D7 for the low (dipper) beam and LED2 on D8 for the high (upper) beam. On a real vehicle these would give way to a relay stage switched through transistor drivers with flyback diodes. As the UNO drives its pins at 5 V while the RC522 is rated for 3.3 V, a level shifter on the SPI and reset lines is advisable. Because the vehicle needs only a reader and a small controller, the design can be fitted to older cars that have neither a camera nor matrix-LED headlamps.

B. Switching Algorithm and Robustness

The controller polls the reader all the time and reacts only to valid tags (Algorithm 1). It starts in low beam at power-on, which is the safe state with respect to glare. A valid entry UID selects (or keeps) low beam, a valid exit UID selects (or keeps) high beam, and any other event, whether an unknown UID or no tag at all, leaves the state as it is, so the lamp never ends up in an undefined state. After each read the

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card is halted and a delay of 100–150 ms (120 ms in firmware) follows so that a tag still inside the field is not handled twice.

Algorithm 1: RFID-based headlight mode switching. An invalid UID is ignored, and the current mode is kept when no tag is detected.

Input: *Tag UID from the MFRC522 reader*

Output: *Dipper mode (LED1) or upper mode (LED2)*

```
Initialise reader and LED pins
Define entry-tag UID and exit-tag UID
loop
    if a tag UID is detected then
        if UID = entry UID then
            LED1 on (dipper), LED2 off
        else if UID = exit UID then
            LED2 on (upper), LED1 off
        end if
    end if
end loop
```

On a two-way road each carriageway needs its own pair of tags with different UIDs, and a tag intended for the opposite direction counts as an unknown UID and is ignored. A deployed system would add checks for UID length, authenticity of protected tag data, membership in the rule table and order of tags. If any step fails, the read is discarded and the last beam mode stays, so each added check can only make the system more conservative.

Software Platform and AI Analytics

Fig. 3 places the system in an IoT frame: tags, reader and controller form the perception layer, a Python bridge and the cloud form the network and application layers, and a dashboard presents the result. Solid boxes are implemented and dashed boxes are planned.

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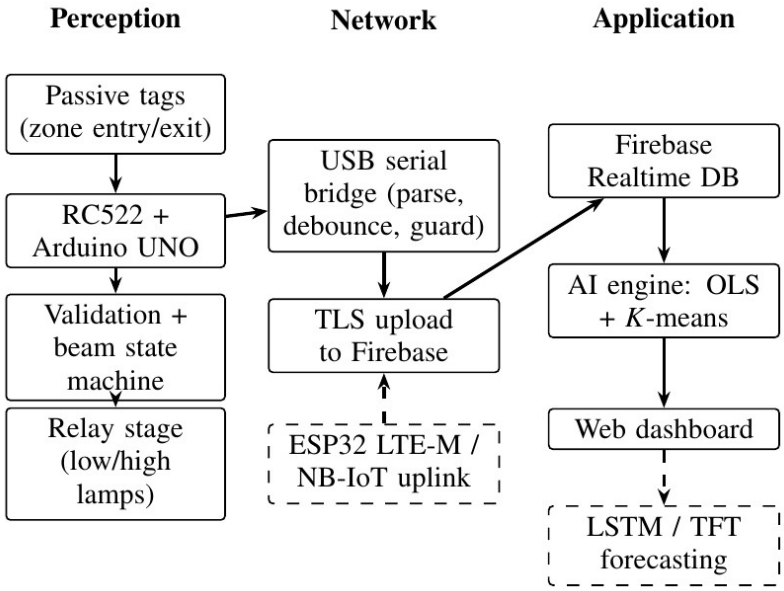


Fig. 3. Layered IoT architecture. Solid boxes are implemented; dashed boxes are planned extensions.

A. Edge Middleware and Cloud

The Arduino reports each read over UART at 9600 baud as a text line such as `Scanned UID: 0x73, 0x21, 0x62, 0x14`. The Python bridge maps each known UID to a card type and a beam command and reports any other UID as unknown with the beam left unchanged. Two checks follow. A scan is dropped when its UID equals the previous UID and the time since that scan is below 2.5 s, and a Boolean variable S_{city} makes the bridge ignore an exit scan while the vehicle is not inside the zone. Every 5 s the bridge writes a heartbeat timestamp t_{hb}, and the dashboard treats the bridge as online only if `bridge_online` is true and $t_{\text{client}} - t_{\text{hb}} < 15000$ ms. Google Firebase Realtime Database [1] holds three nodes: `/state/current` for the present beam and bridge status, `/events` as an append-only record of every accepted scan with hour, day, card type and UID, and `/ai_insights` for the analytics output written every 60 s.

B. Traffic Analytics

A separate analytics process, built with scikit-learn [22], counts the entry events per hour into a vector $\mathbf{V} = [v_0,\ldots,v_{23}]^{\mathsf{T}}$ so that model fitting never delays the beam path. A straight line $\hat{y}(h) = wh + b$ is fitted by ordinary least squares [23],

$$\theta^{*} = (\mathbf{H}^{\mathsf{T}}\mathbf{H})^{-1}\mathbf{H}^{\mathsf{T}}\mathbf{V}, \tag{1}$$

where $\mathbf{H}$ has rows $[h, 1]$ and $\boldsymbol{\theta} = [w, b]^{\mathsf{T}}$, and the next-hour count is predicted at $(h_{\text{now}} + 1) \bmod 24$, rounded and kept non-negative. A single line cannot capture a morning and an evening peak, so the

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model is a trend indicator and not a predictor. To label traffic without hand-set thresholds, the hourly counts are divided into $k = 3$ groups by K-means [25],

$$\arg\min_{S} \sum_{j=0}^{2} \sum_{v \in S_j} \|v - \mu_j\|^2, \tag{2}$$

solved with Lloyd's iteration [24]. Raw cluster numbers depend on initialisation, so the centroids are sorted and the lowest becomes *Off-Peak*, the middle *Normal* and the highest *Rush Hour*; ten restarts and a fixed seed make the result repeatable.

C. Dashboard and Demonstration

A single-page web dashboard (Firebase JavaScript SDK and Chart.js) shows the live beam, the last UID and event, the last 20 events and the analytics. The analytics were demonstrated on synthetic traffic from a generator script that builds 14 days of arrivals from Poisson and Gaussian profiles, because no real roadside deployment exists yet. Fig. 4 shows the result. The hours around 08:00–10:00 and 17:00–19:00, with roughly 350 to 510 entries per hour, form the Rush Hour group, hours with fewer than about 30 entries form the Off-Peak group, and the rest are Normal. The fitted line rises from about 90 to about 300 entries per hour and passes through the two peaks without following them. Since the data are synthetic, these figures show that the pipeline works from event to chart; they say nothing about real traffic.

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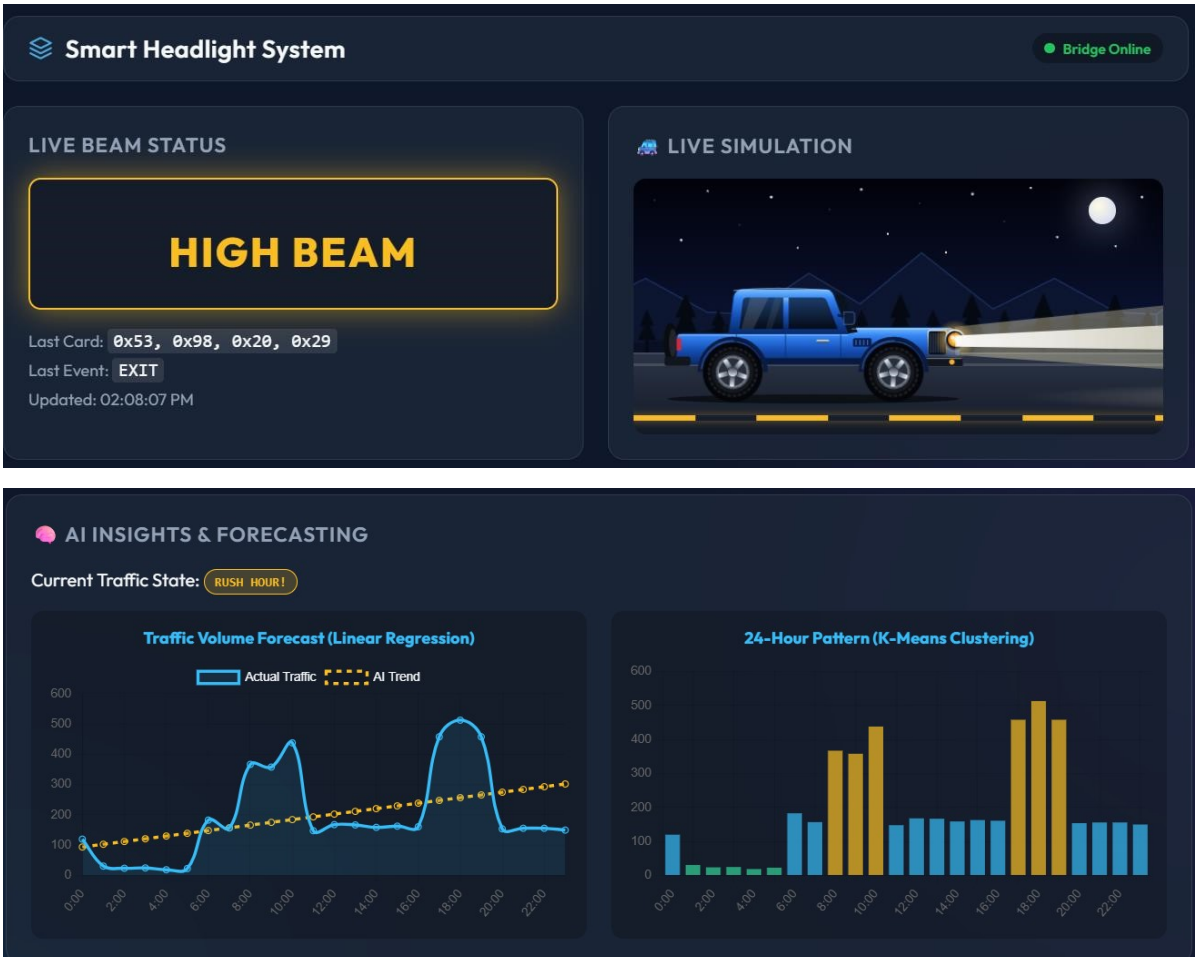


Fig. 4. Top: dashboard with live beam status, last card UID and bridge-online badge. Bottom: AI insights on synthetic data, with the linear trend and the three K-means traffic regimes.

Evaluation Plan and Read-Window Analysis

The next stage will measure the beam-switching accuracy $A = N_c/N_t$, the read success rate $R = N_r/N_t$ and the false-trigger rate $F = N_f/N_t$, where N_t is the number of tag passes, N_c those with the correct beam state, N_r those in which the tag was read and N_f the beam changes caused by an invalid UID or no tag, together with the latency $L = t_{\text{lamp}} - t_{\text{read}}$ and a 95% confidence interval. Test cases T1–T8 cover entry, exit, unknown and absent tags, a tag held in the field, and the effect of distance, speed, cover and dust; a logic probe on D7 and D8 will timestamp the output. End-to-end latency, silhouette coefficient and mean absolute error of the software will be measured on recorded field data. No hardware measurements are reported in this paper.

If the effective read range is r and the vehicle passes the tag at speed v, the tag is inside the field for about

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$$t_w \approx \frac{2r}{v}, \tag{3}$$

and a dependable read needs t_w to exceed the time the reader takes to read the tag. Table 3 gives calculated values for 5 cm, typical of a short-range 13.56 MHz reader, and 30 cm, the range reported for the UHF road-embedded prototype in [12]. A short-range reader therefore suits slow zones such as toll plazas, junctions and slow stretches, while highway speeds need longer range or a faster read rate; tests T6 and T7 will replace these assumed values.

Table 3. Illustrative Read Window t_w (ms) for Assumed Ranges

Range *r*	**20 km/h**	**60 km/h**	**100 km/h**
5 cm	18	6	3.6
30 cm	108	36	21.6

Security, Cost and Limitations

The 13.56 MHz tags read by the RC522 are not secure by default, and a plain UID can be copied; classic MIFARE cards use a cipher with known weaknesses. A cloned tag could force the wrong beam, so a deployed system needs authenticated tags and should read protected data, not only the UID. A removed tag is covered by the fail-safe and periodic inspection, out-of-order tags by accepting an exit tag only after an entry tag, radio interference by retries and shielding, and controller or bridge faults by a manual driver override and the heartbeat watchdog. The beam must never be left unsafe after a missed exit tag, so a second source of evidence such as an ambient-light sensor is recommended. The tags carry only a zone identifier and no personal data.

Roadside cost grows with the number of zones and vehicle cost with the number of equipped vehicles:

$$C = n_z\,(2c_t + c_i) + n_v\,c_k, \tag{4}$$

where n_z is the number of zones, c_t the cost of one tag, c_i the installation cost per tag, n_v the number of equipped vehicles and c_k the cost of one vehicle kit. Passive tags are cheap, so installation and replacement of damaged tags are likely to dominate.

Compared with camera, AI and LiDAR/radar systems, which are costly and hard to retrofit, and LDR methods that sense only local light, the proposed approach is expected to be low cost, independent of fog, rain and oncoming glare, and easy to fit to older vehicles. It suits places where the lighting changes at a known point, such as a lit urban stretch, a tunnel mouth, a toll plaza, a junction, a bridge approach or a sharp curve. The comparison is qualitative and based on the characteristics reported in the reviewed papers. There are practical limits. The 13.56 MHz reader has a short range, so the prototype shows the control logic and not a full highway deployment, and longer-range UHF readers would be needed at speed, although the UHF prototype in [12] reports only about 30 cm in road conditions. Beam control exists only on roads that carry tags, and the system does not sense an oncoming vehicle directly. The

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bridge is wired, the dashboard needs an internet connection, and the analytics have so far been run only on synthetic data.

Conclusion and Future Work

This paper presented the motivation, literature survey, research gaps and design of an RFID-based automatic headlight controller for glare-free night driving on highways. The twenty studies from 2021 to 2026 show that camera, LiDAR, radar and AI-based systems are accurate but costly, that LDR-based systems sense only locally, and that RFID is widely used in intelligent transportation but not for headlights. The proposed Arduino UNO and RC522 system aims at this gap with a low-cost, weather-independent, retrofit-friendly approach that relies on infrastructure, and a cloud software platform adds remote monitoring and traffic analytics, shown here on synthetic data only. In the next stages the hardware will be built and tested for accuracy, response time, read range, tag security and reliability. Planned extensions are longer-range UHF readers, authenticated tags, an on-board ESP32 module with an LTE-M or NB-IoT uplink, sequence models such as LSTM or temporal fusion transformers with weather inputs, and a camera for matrix dimming.

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