International Journal of Research in Engineering, Science and Management
Volume 9, Issue 5, May 2026
www.ijresm.com | E-ISSN: 2581-5792 | RESAIM Publishing | www.resaim.com

Multi-Variable Traffic Control: Simulating the Impact of Weather and Incidents via Type-1 Fuzzy Logic

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***Abstract*: Basic The effective management of urban traffic remains an important obstacle, due to the dynamic and probabilistic nature of typical urban settings. Conventional traffic control systems, which are primarily based on fixed-timing or simple sensor-actuated adaptive mechanisms, frequently disregard external factors such as adverse weather conditions and unexpected road incidents. In this research, a multi-variable traffic control framework is proposed. The system is designed to maximize the intersection throughput by incorporating the multiple variables into the fuzzy logic simulation system. The developed system uses fuzzy logic controller that can handle the linguistic variables and non-linear inputs. Inputs are traffic density, precipitation intensity, visibility conditions, and incident severity. The controller employs a large set of rules to adaptively adjust signal timings to compensate for the reduced roadway capacity and longer stopping distances that are common in rain or fog. Simulation analyses were carried out to evaluate the performance of the fuzzy logic model compared to the existing control methods. The results demonstrate that the multi-variable fuzzy strategy performs significantly better than conventional methods, particularly under peak demand and extreme weather conditions.**

***Keywords*: Enter Fuzzy Logic, Smart City, Type 1 Fuzzy Logic, Traffic Management, Weather Simulation, Control systems.**

1. Introduction

One of the attributes of the twenty-first century has been the rapid urbanisation that has seen cities across the world experience unprecedented population growth and infrastructure development. This demographic shift has led to exponential growth in vehicular traffic, overwhelming road networks and resulting in severe congestion, economic losses, elevated emissions, and reduced productivity. The needs of urban mobility cannot be met by traditional infrastructure expansion alone [1].

Contemporary traffic management systems rely on the outdated paradigms that are ill-suited to modern complexities. Fixed-time traffic lights follow predetermined schedules regardless of the real-time conditions, while standard GPS navigation aids individual routing but fails to coordinate intersections or adapt to dynamic anomalies like weather shifts or accidents. These rigid approaches falter during peak hours or adverse conditions [2].

Intelligent Transportation Systems and Smart Navigation Systems provide promising solutions via advanced sensing and computation. A study demonstrated camera sensors with algorithms for bounding box-based traffic density estimation, allowing for dynamic lane priority and data-driven control without fixed-time constraints [3].

But traffic flow is not linear. It's influenced by subjective factors such as rain (which reduces visibility and braking distances) or incidents that create bottlenecks. Binary logic has a difficult time dealing with such ambiguity and varying degrees of certainty [4].

This paper addresses these gaps with a multi-variable Fuzzy Logic controller that imitates human reasoning to manage unclear inputs. It combines Traffic Density, Rainfall Intensity, and Incident Severity through a fuzzy inference system for precise signal timing adjustments.

2. Literature Review

A. *The Evolution of Traffic Management Systems*

The foundation of modern traffic control systems is fixed-time signal controllers. These controllers run on pre-programmed timing cycles based on historical traffic data. Although these systems are widely used because they are simple and inexpensive to implement, they have a significant drawback. They cannot adjust to changing traffic conditions. Fixed-time methods set signal phase durations based on average historical volumes. This approach is not effective for handling the varying arrival rates of vehicles at intersections [5]. The main issue with fixed-cycle approaches is that they cannot respond to traffic changes in real-time. This often worsens congestion when traffic patterns shift unexpectedly [6]. Under unusual traffic conditions or special events like incidents or extreme weather, these systems show their limited flexibility and ability to adjust. They cannot change signal plans based on current demand [7]. Secondly, a statically timed traffic signal programmed with fixed numerical time values will cycle red and green indiscriminately, regardless of actual traffic conditions. Consequently, there is considerable wasted time at peak and off-peak hours [7].

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Driven by the shortcomings of fixed-time traffic control, it has now undergone a transformation into intelligent transportation systems, where cutting-edge sensor and communication technologies can control traffic in real-time. Intelligent transportation system is the combination of IoT, ICT and data mining technology for the collecting and processing traffic information in real-time through different communication standards and technology enablers [8]. Nowadays, modern sensors such as inductive loop detectors, microwave radar sensors, Bluetooth detectors and cameras allow real-time analysis of traffic flow, counting vehicles, determining their speed, and identifying traffic incidents [9]. Wireless Sensor Networks (WSNs) look very suitable for ITS applications provide very low cost, easy implementation, and embedded sensing, computing and wireless transmission[10]. These are used to enable traffic and location information to be broadcast in real-time, thus helping travellers optimize travel time and costs and reducing both fuel consumption and vehicle emissions [11].

B. Environmental and Situational Impacts on Traffic Flow

Many adverse weather phenomena are known to degrade traffic performance, not least because of the effect on precipitation, and the impacts are diverse. The fundamental relationship between traffic flow parameters is captured by Greenshields' foundational macroscopic flow model, which establishes the relationship between traffic flow (q), density (k), and vehicle speed (v) using the fundamental equation:

$$q = k \cdot v$$

Studies evaluating environmental impacts often modify Greenshields' linear speed-density relationship to account for wet weather conditions. The standard model dictates that velocity decreases as density approaches jam density (k_j):

$$v = v_f \left(1 - \frac{k}{k_j}\right)$$

Where, v_f represents the free-flow speed [13].

Quantitative studies have consistently shown that rainfall intensity correlates strongly with capacity reduction. Light rain (intensity of 0.01-0.25 inches/hour) decreases freeway capacity by 4-10%, while heavy rain (intensity of 0.25 inches/hour or greater) decreases freeway capacity by 25-30%. The presence of rain, regardless of intensity, results in approximately a 5.0-6.5% average decrease in operating speeds [13]. These findings indicate that the impact of rain is more significant than currently reported in standard capacity manuals, necessitating careful examination of traffic operations strategies during rainfall events.

C. Incident Based Congestion

The third major group of events, and a type of event that has a strong impact on traffic situation and causes rapid traffic saturation at an intersection, is road accident (including crash, accident, breakdown, and necessary road works). Road accident leads to blocked operation for the specific section, interchange, or intersection, with some variations of traffic situation based on network parameter changes: capacity and average speed for specific road section. Traffic incidents result in reduced road capacity that varies according to road type configuration and lane blockage number. Studies indicate that a lane blockage in a two-lane freeway road case significantly reduces road capacity [14].

From the empirical analysis to estimate the effect of several traffic accident types on speed and maximum flow. The traffic accidents with significant impact effects include a breakdown vehicle, accident, and rain [15].

D. Existing Fuzzy Traffic Models

Given the intrinsic complexity and fuzziness of traffic situations, an increasing number of research on traffic control have switched to using fuzzy inference system instead of binary logic for transport networks [16]. Traffic density itself cannot be defined with exact values (i.e., binary values), traffic density is rather subjectively perceived rather than objective [4]. The characteristic of fuzzy logic of 'truth values are truth values' means they can take on values from 0 to 1, thus it is ideal for controlling the flow [17]. The inputs are mapped to outputs by linguistic values which are distributed to fuzzy sets-for instance, describing the amount of traffic as low, medium, high-which have membership functions describing how much each fuzzy set is influenced [18].

Using this method, a value can belong to several fuzzy sets at the same time [16]. This better represents real traffic situations.

Various fuzzy logic intersection control systems have been proposed in the literature; they typically use queue length, waiting time, and road density as input to fuzzy controllers [18]. In one approach, an integrated system of fuzzy rules and image processing utilizes cameras to evaluate red phase queue lengths and green phase arrival rates on a per lane basis. Min-max inference and centroid defuzzification are employed to determine green light duration [19]. Road density is taken as input and green duration is taken as output for a model of this kind with triangular membership functions, density being taken in the range 0-22 vehicles and duration in the range 0-18 seconds, with linguistic values such as Low, Medium, and High [20]. Another incorporates per-lane traffic and emergency vehicle presence, weighting inputs for decisions [21].

The Mamdani fuzzy inference system is widely applied in this application field. In Mamdani fuzzy system, Mamdani fuzzy implications are applied to predict the number of vehicles and green light time at intersection. Input data are the motorcycles, light vehicles, heavy vehicles, and time [22]. Membership functions in such systems typically use triangular forms, with equations defining membership degrees for different queue lengths [23]. For example, membership functions for queue length might be defined as:

$$f(q) = \max\left(\min\left(\frac{5-q}{5}, 1\right), 0\right)$$

for "zero" vehicles, with similar formulations for "a few," "medium," and "long" queues [23].

Standard Mamdani fuzzy inference usually involves evaluating each of the rules in order, using minimum t-norm operators, for each rule to calculate a degree of firing using the intersection of the membership degrees of the inputs [24], [25]. This approach, while theoretically sound, can become computationally expensive as the number of rules and input variables increases.

The standard Mamdani fuzzy inference process evaluates the firing strength $(\alpha)$of the i-th rule using the minimum t-norm operator:

$$\alpha_i = \min\left(\mu_{density}(x), \mu_{rainfall}(y), \mu_{incident}(z)\right)$$

where μ represents the membership degree for each input variable [25]. These sequential computations along with fuzzy centroid calculations cause computationally expensive points of which multiple variables cannot be calculated in real time on high sampling frequencies [26]. The result would be a system with the real time, adaptive control based on all conditions effecting intersection performance, rather than a single input, as most current fuzzy traffic models proceed [27], [28]

3. Methodology

The approach of this research will be based on developing an "off-the-shelf" Mamdani type Fuzzy Inference System for high-performance computing in smart cities. Unlike models which run in an iterative manner, the proposed controller is completely vectorised in order to deal with the high-performance data that arises from real-time sensor inputs with a low computational overhead.

A. System Architecture and Parameter Selection

The controller is designed to take three inputs and to produce a single crisp output as the green light time. These three inputs were chosen as they represent the most important stressors from traffic literature:

1. *Traffic Density* (D)*:* Ranging from 0% to 100%, this parameter represents physical road saturation. It utilizes the bounding-box vehicle counting methodology established in a 2020 study [29].
2. *Rainfall Intensity* (R): Ranging from 0 to 50 mm/hr, this environmental parameter accounts for the documented reduction in road capacity during heavy precipitation [30].
3. *Incident Severity* (I): Measured on a scale of 0 to 10, this situational parameter quantifies the impact of unpredictable events, such as accidents or breakdowns, which can reduce lane capacity [31].
4. *Green Light Duration* (T): The output variable is restricted to a mathematically safe operational window of 10 to 60 seconds to maintain network synchronization.

B. Fuzzification Strategy

To ensure computational efficiency for edge computing, the system employs piecewise linear membership functions. We utilize Triangular (μ_{tri}) and Trapezoidal $\left(\mu_{trap}\right)$ functions, which allow for rapid degree-of-membership calculation without the overhead of Gaussian models [18].

The mathematical formulation for these functions, supporting matrix-based input, is defined as:

$$\mu_{tri}(x; a, b, c) = \max\left(\min\left(\frac{x-a}{b-a+\epsilon}, \frac{c-x}{c-b+\epsilon}\right), 0\right)$$

$$\mu_{trap}(x; a, b, c, d) = \max\left(\min\left(\frac{x-a}{b-a+\epsilon}, 1, \frac{d-x}{d-c+\epsilon}\right), 0\right)$$

Where, ϵ is a machine-epsilon constant to prevent division-by-zero errors. Each input variable is partitioned into three linguistic sets (e.g., Density: Low, Medium, High) [32] to bound the universes of discourse effectively.

C. Vectorised Rule Base and Inference Engine

The technical core of the controller is its vectorized inference engine.

The logic utilizes the minimum t-norm operator for rule evaluation. The three primary weighted outputs are calculated as follows:

1. *Short Duration* (w_{short}): Primarily driven by low traffic density.
2. *Standard Duration* (w_{stand}): A complex intersection of medium density and clear-to-light rain conditions.
3. *Extended Duration* (w_{ext}): Triggered when high density intersects with heavy rainfall $(D \geq 60\%, R \geq 15mm/hr)$.

D. Defuzzification Engine

After rule evaluation, the fuzzy firing strengths must be converted into a precise signal time. This system employs the Weighted Average Method to ensure a smooth output surface and prevent abrupt timing transitions. The final crisp green light duration $\left(T_{green}\right)$ is calculated by multiplying the firing strengths by their respective output centroids $(w_1 = 17.5s, w_2 = 35s, w_3 = 55s)$:

$$T_{green} = \frac{\sum_{i=1}^{n} \alpha_i \cdot w_i}{\sum_{i=1}^{n} \alpha_i}$$

where n represents the total number of rules in the activated set. A fallback logic is implemented to maintain a baseline of 15 seconds if total rule weight is zero, ensuring system stability.

E. Simulation and Validation

The logic is validated through two high-resolution procedures:

1. *Fuzzy Inference Surface*: A 3D topological plot is generated using a meshgrid approach to verify the non-linear transitions between density, rainfall, and signal duration.

2. *Real-Time Time-Series Simulation*: The simulation running for 1000 steps provides a worst-case test for the controller using noisy sensor values and an environmentally simulated 'weather shock' (a large spike to 40 mm/hr). From the simulation, we can see the controller is capable of momentarily ignoring density-following curves to force the use of safety-critical time stamps in extreme conditions [13], [14]

4. Results and Discussion

A. Validation of Fuzzification and System Boundaries

Figures 1 through 4 illustrate the fuzzification parameters of the proposed controller. Traditional computational logic is inherently binary; a value is either 0 or 1, which in a traffic system can lead to rigid and inefficient transitions—for instance, where a density of 49% triggers a "short" light while 50% triggers a "long" light. By contrast, this Mamdani-type system mimics human reasoning by introducing "degrees of truth," where a crisp sensor reading can belong to multiple linguistic categories simultaneously [33].

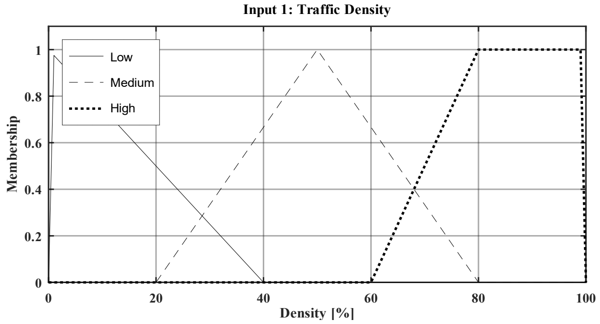

Fig. 1. Translates physical road saturation (0–100%) into Low, Medium, and High

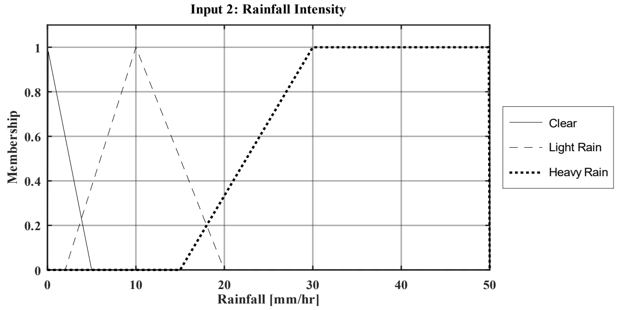

Fig. 2. Translates precipitation levels (0–50 mm/hr) into Clear, Light Rain, and Heavy Rain

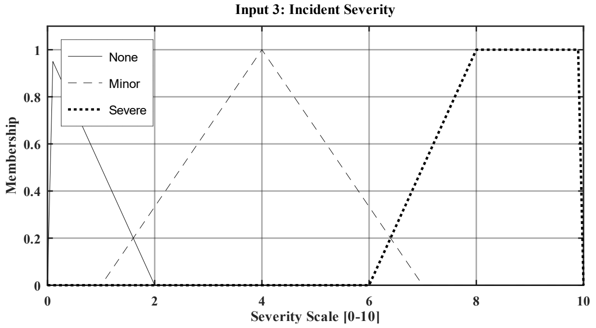

Fig. 3. Translates a severity scale (0–10) into None, Minor, and Severe

To ensure computational efficiency suitable for real-time edge-computing environments, triangular and trapezoidal membership functions were selected to map crisp inputs into overlapping linguistic sets [34]. This deliberate overlap is critical; it prevents the volatile, binary thresholding that plagues traditional traffic algorithms, allowing the system to calculate weighted, proportionate responses to ambiguous environmental states.

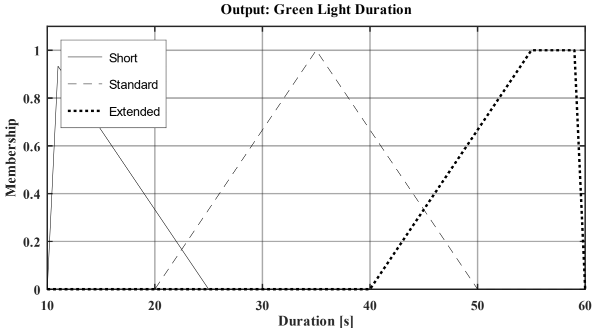

Fig. 4. Defines the output universe, mapping the fuzzy results to a mathematically safe window of 10 to 60 seconds

B. Topological Analysis of the Interference Surface

Figure 5 plots the fuzzy inference surface, which confirms the mathematical stability of the vectorised rule base. This 3-D view shows the entire mathematical functioning of the defuzzification engine as a function of both the inputs (Traffic Density and Rainfall) and the final output (Green Light Duration). The surface maps the system topology and clearly illustrates that there are no discontinuities or jagged “cliffs” (which represent mathematical instability and contradictions between rules). Most importantly, the surface clearly represents the safety over-ride logic. Under fair weather conditions the system output steadily increases with both the number of vehicles and the time interval.

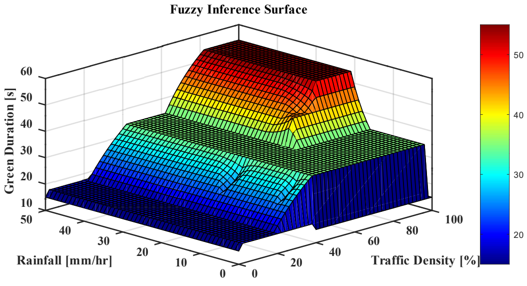

Fig. 5. Fuzzy interference surface plot

As rainfall increases to the aforementioned critical level (e.g., On the left-hand side of the contour where Rainfall > 30 mm/hr), however, the surface becomes flat in a plateau of high-duration Green Light Time. The rule base then monotonically increases from moderate Traffic Density readings to the highest 55-sec clear phase where moderate Traffic Density does not produce significant effect on the final green light time value. This is consistent with the general decreased ability of vehicles to brake during heavy rain [35], and the resultant reduction in system capacity by 2.46-12.97% [30].

C. Dynamic Responsiveness and Situational Adaptability

To evaluate the real-time responsiveness of the controller, a time-series simulation was conducted by subjecting the system to high-frequency vehicular noise and a sudden-onset environmental anomaly. The simulation acts as an oscilloscope, demonstrating the system's cause-and-effect relationship over 1000 discrete time steps.

As observed in the panels of Figure 6, the controller exhibits two distinct operational modes:

1. *Numbering Efficiency Optimization Phase*: Between the initial time steps, the calculated green light duration (the thick black line in the bottom panel) dynamically tracks the chaotic fluctuations in traffic density (top panel), optimising intersection throughput under standard conditions.
2. *Safety-Critical Phase*: Following the introduction of a severe rainfall event spiking to 40 mm/hr (middle panel), the fuzzy inference engine reacts instantaneously. The output duration immediately decouples from the standard density-following curve and escalates to the maximum extended phase.

This phase shift conclusively demonstrates that the multi-variable controller can autonomously prioritise intersection safety over standard throughput metrics during sudden crises. [14] This is particularly vital given that situational incidents can reduce road capacity by up to 68%.

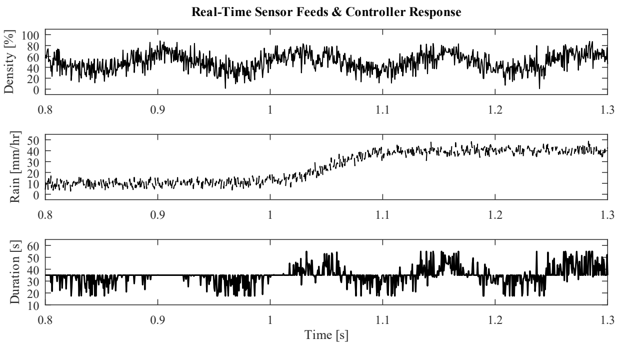

Fig. 6. Real-time responsiveness of the controller

D. Comparison with Traditional Paradigms

These figures illustrate how macroscopic models, such as Greenshields' linear relationship [36], [37], cannot accurately describe the dynamic variation of free-flow speed in response to external stimuli like water film depth [36]. However, proponents argue that such models remain valuable for their computational simplicity, interpretability, and effectiveness in stable conditions without adverse weather, serving as reliable baselines for large-scale simulations and preliminary planning. Our findings confirm that capacity is not a static value but a fluctuating variable that can drop by as much as 42.27% in adverse weather [38].

By utilising a vectorised matrix approach, the system calculates the firing strength of every rule simultaneously using the minimum t-norm operator, avoiding the computational lag of iterative loops [39]. This makes the controller exceptionally fast and suitable for real-time deployment in smart-camera-equipped intersections [29]. The integration of these variables ensures that the infrastructure remains resilient, bridging the gap between theoretical traffic physics and practical, real-time control [25].

5. Conclusion and Future scope

This paper proposes a vectorized multi-variable fuzzy logic controller for urban intersection traffic control under changing environment, which successfully maps inputs-Traffic Density, Rainfall Intensity and Incident Severity-to Green Light Duration using triangular/trapezoidal membership functions [18], [23] By integrating these variables, it overcomes limitations of fixed-time and single-variable systems, mimicking human reasoning to handle uncertainty and address capacity drops from adverse weather (e.g., up to 32.5% flow reduction and 25-30% freeway capacity loss in heavy rain[13], [36]) and incidents.

Simulations validate robustness: under low density (<40%) and negligible rain, baseline green duration holds at ~15 seconds, but safety override activates above 30 mm/hr rainfall, extending to the 55-second maximum despite moderate density, compensating for increased headways and reduced speeds [13]. Time-series analysis of high-frequency noise and shocks (e.g., 40 mm/hr storms with incidents) shows instantaneous adaptation, detaching from density curves to mitigate ~68% capacity loss from blockages [14], [40] unlike fixed-time paradigms.

The vectorized matrix ensures smooth inference surfaces free of discontinuities, enabling parallel rule evaluation for low-latency edge deployment [41], [42]. Compared to macroscopic models like Greenshields' ($\mathrm{v_f} - \mathrm{k_j}$ relation [37]), it dynamically adjusts for weather-induced v_f drops [38], bridging theory and real-time control.

It provides a safe and effective, scalable platform for sustainable urban transport, yielding higher throughput, safety, and faster reaction times. Work to this will be continued with interconnected intersections for optimization across the whole corridor.

While the proposed system provides a robust solution for real-time traffic management, there are several avenues for future enhancement:

1. *Numbering Transition to Type-2 Fuzzy Logic*: The presented system currently implements Type-1 fuzzy logic where, to define fuzzy values, we are using two-dimensional, crisp membership functions. Though capable of producing satisfactory results, Type-1 systems do not really "know what they know, and what they don't know", i.e., in such stochastics systems, the linguistic uncertainty and the sensor's noise vary in a complex manner that is not easy to be described by Type-1 [18]. Future extensions of this work will include consideration of Type-2 Fuzzy Logic, which takes this concept of a "Footprint of Uncertainty" even further. This higher order logic can more reliably model noise, and a more stable control surface can be formed under the unreliable conditions of the sensor

data [25].

2. *Computational Trade-offs*: The main motivation of adopting a Type-1 model in this research was the need for a light and low-latency system. Thanks to vectorised Type-1 logic we could evaluate simultaneously the rules on large data-grids without the computational drawbacks that exist for iterative fuzzy models [39]. However, type-2 fuzzy logic is far more computationally complex than its counterpart and as a result either relies upon complex optimization methods or is executed on specialized hardware to facilitate real-time performance [43]. With increase in capabilities of edge-computing power, transition to Type-2 models can be implemented and the need for handling the uncertainty with good high frequency response, as needed in case of traffic signals, will be catered.
3. *Network-Wide Coordination*: Future work should also build this logic to create a networked, decentralized system. By letting nearby controllers exchange their respective "incident" and "weather" fuzzy states, a green wave can be created across an entire corridor, taking hazards into consideration, reducing urban congestion, and increasing network robustness.
4. *Sensor degradation*: One potential long term stability issue with this controller is that physical sensor degradation and noise in the transmission data are not addressed. This is to say that in practice, actual sensor ranges tend to decrease over time or the physical sensor can degrade due to physical elements over time.

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