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Adaptive Q-Learning for Safety Message Priority in Vehicular Fog Computing Based on Indonesia Transportation and Weather Data

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ABSTRACT

The development of Intelligent Transportation Systems demands fast, adaptive, and reliable communication mechanisms between vehicles, especially when the system has to process multiple emergency events simultaneously. This article proposes an adaptation of the Adaptive Q-Learning model for the priority dissemination of safety messages in the Vehicular Fog Computing environment by utilizing the context of Indonesian data. Adaptation was made to the Q-learning design based on incident priority, but modified in terms of state, action, and reward variables to match the characteristics of Indonesia's urban transportation, especially DKI Jakarta and national data. The data sources mapped in the model come from the Central Statistics Agency's Land Transportation Statistics, Jakarta Statistics Profile, and BMKG Open Weather Forecast Data. State agents are built from a combination of bucket delay, traffic density level, weather conditions, trust node scores, and types of safety events such as ambulances, accidents, road hazards, and inundation. Action space is represented as a choice of different Quality of Service weights to balance delay, packet delivery ratio, trust, and energy efficiency. The reward function is designed to give higher priority to stacked emergencies while penalizing delays and energy consumption. The results in the tables and graphs in this article are presented as an illustrative simulation based on a methodology design, not the results of direct field tests. With this approach, this article offers a relevant, original, and contextual research framework for the development of intelligent transportation systems in Indonesia.

1. Introduction

Digital transformation in the transportation sector has transformed the way modern mobility systems manage safety information, travel efficiency, and response to emergencies. In big cities like Jakarta, the heavy flow of vehicles, the diversity of transportation modes, and the influence of tropical weather make the decision-making process on the transportation network very dynamic. In such an environment, delays in sending safety messages can have a direct impact on increased response times, decreased information reliability, and increased risk of secondary accidents. Therefore, vehicle communication systems no longer rely enough on static rules or fixed priorities but instead require adaptive and context-aware decision-making mechanisms [1], [2], [3].

Vehicular Fog Computing offers a near-data source computing approach by leveraging vehicles and edge nodes as part of the computing infrastructure. This paradigm is interesting because it can reduce reliance on centralized clouds, lower latency, and accelerate the distribution of safety messages [4], [5], [6]. However, VFCs also face major challenges in the form of rapidly changing topologies, unstable connection quality, energy limitations on certain nodes, and differences in trust levels between participants in the network. When several critical events occur at about the same time, such as an ambulance passing through a traffic jam during heavy rain and an accident or inundation, a simple priority system will struggle to maintain consistent performance [1], [2], [7], [8].

One of the increasingly popular approaches to address policy adaptation problems is reinforcement learning, specifically Q-learning. Q-learning allows agents to learn the best course of action for each state condition without having to have a complete environment model from the start. In the context of smart transportation, this approach is promising because agents can adjust messaging strategies based on a combination of traffic conditions, network quality, type of incident, and operational risks. The reference article that is the inspiration in this paper shows that Q-learning combined with rewards based on incident priority, trust, and energy can improve the performance of spreading safety [9], [10], [11]

Several previous studies have provided the foundation for this research. Prior work on vehicular fog and edge computing has shown that placing computation closer to vehicles can reduce latency and improve responsiveness for traffic-related applications. In addition, studies on reinforcement learning, particularly Q-learning and its reward-based variants, have demonstrated their potential for adaptive decision making in dynamic network environments, including message dissemination and priority control. However, most of these studies were developed in general simulation settings and were not specifically designed for the Indonesian transportation context. They do not explicitly incorporate local factors such as traffic density, road-speed variation, rainfall intensity, flooding potential, and the characteristics of official Indonesian transportation data. This limitation reveals a clear research gap and provides the main justification for the present study.

However, this approach still requires strong adaptation if it is to be used in the Indonesian context. The characteristics of Indonesia's data are not only characterized by the volume of vehicles and traffic accidents, but also by weather factors, the potential for flooding or inundation, as well as variations in road speed during peak hours. The Central Statistics Agency routinely publishes Land Transportation Statistics which contain data on roads, motor vehicles, accidents, driver's licenses, and rail transportation. At the regional level, the Jakarta Statistical Profile provides an indicator of the average speed on roads affected by traffic restrictions. On the other hand, BMKG provides open weather forecast data up to the sub-district or village level, so it is very likely to be used as a contextual variable in the message priority model [12], [13].

Based on this gap, this study proposes an adaptive Q-learning model for safety message prioritization in vehicular fog computing by integrating Indonesian transportation and weather-related variables into the state and reward design. The novelty of this study lies in the contextual adaptation of the previous method, not merely by replicating the existing framework, but by extending it with locally relevant data and event conditions such as rainfall and flooding. Through this approach, the study is expected to provide a more realistic and practically relevant contribution to intelligent transportation research in Indonesia [9], [12], [14].

Thus, this article does not simply replicate the previous method but builds a more contextual and more accountable version for Indonesia's transportation environment. The structure of the writing is structured like a journal article, starting from an introduction, literature review, methodology, illustrative design and simulation results, discussion, conclusion, and IEEE-style bibliography.

Vehicular Fog Computing

Vehicular Fog Computing views vehicles not only as network users, but also as computing, communication, and storage nodes that can work collaboratively. This idea is important because modern transportation applications are sensitive to latency [6], [15], [16]. Messages related to safety, route diversion or coordination of priority vehicles should be processed as close to the scene as possible. With this model, decisions don't have to wait for a response from a distant data center [17], [18], [19]. Vehicles, roadside units, and edge nodes can jointly handle compute loads according to available connectivity capacity and conditions [1], [20], [21], [22].

Surveys on VFCs show that this paradigm is effective for supporting applications such as accident alerts, path navigation, offloading computing tasks, and real-time traffic management. However, the VFC environment has specific challenges. Nodes are highly mobile, connection durations can be short, resource distribution is uneven, and the risk of service quality degradation increases during heavy traffic or inclement weather. Therefore, the mechanism for prioritizing messages and selecting delivery strategies should consider more than one QoS metric [2], [3], [23].

1.1. Q-Learning and Prioritas Pesan

Q-learning is a model-free reinforcement learning algorithm that updates action values based on the experience of interaction with the environment. The agent selects an action, receives a reward, and then updates the Q-value table to get closer to the optimal policy. The main advantages of Q-learning are its simplicity, high interpretability, and are suitable for discrete states. In a transportation safety system, simplicity is an added value because decisions need to be taken quickly and sometimes run on limited resources. Compared to the deep reinforcement learning approach, tabular Q-learning is also easier to explain in academic writings in the early stages of system development [10], [11].

Q-learning is particularly relevant for message priority issues because it is essentially the process of selecting the best action under ever-changing conditions. The state can consist of a combination of delay, trust, energy level, type of incident, traffic density, and weather. Actions can be understood as the choice of QoS weights or decisions of which nodes should process and forward messages. The reward that the agent receives should reflect the quality of the decision, for example it would be better if the emergency message arrived faster, remained reliable, and did not drain excessive energy [9], [11], [24].

1.2. Reference Articles and Modification Rooms

A reference article by Tripura and colleagues proposes Q-APERF, which is a tabular model of Q-learning with the Augmented Priority-Entropy Reward Function. The model combines event priority, QoS score, entropy bonus for exploration, and energy penalty. This structure is particularly interesting because it is scientifically easy to replicate: the problem is clear, the state is discrete, the action space is limited, and the rewards are rich enough to encourage policy adaptation. However, the reference article is not built specifically on the characteristics of Indonesian transportation. Incidence variables still focus on ambulances, accidents, and general road hazards, while dominant conditions in urban Indonesia such as inundation and the impact of heavy rain have not yet become explicit components in the event scaler [1], [2], [25].

In terms of data sources, the reference article emphasizes network simulation and does not specifically associate the state design with the public statistical sources of a country. This is where the modification space is done in this article. Adaptation is done not by copying sentences or results, but by imitating the structure of scientific thinking. The model is maintained at the tabular Q-learning level because it remains relevant, and then changed in terms of data mapping, event definition, and interpretation of operational variables. With this strategy, the final result remains original and in accordance with the Indonesian context.

1.3. Research Gaps

Table 1. Existing research approaches and their limitations

Ref	Approaches	Objectives	Methods	Limitations
[9]	Adaptive event-prioritized QoS optimization in vehicular fog networks	Improve emergency message dissemination by balancing urgency, trust, QoS, and energy	Tabular Q-learning with APERF reward shaping	It is not yet specific using the context of the Indonesian dataset and local weather factors
[11]	Classical Q-learning for adaptive decision making	Learn optimal action policies through environment interaction	Model-free tabular Q-learning	Limited state representation and sensitive to discretization
[10]	Deep reinforcement	Handle complex and high-	Deep Q-Network	More computationally heavy

	learning for control optimization	dimensional decision spaces	(DQN)	and less interpretable for lightweight nodes
[1]	Vehicular fog computing as distributed infrastructure	Utilize vehicles as computation and communication infrastructure	VFC architecture and capability analysis	Focus more on architecture than safety message priority
[2]	Survey of vehicular fog computing	Summarize VFC architecture, services, challenges, and future directions	Systematic literature survey	Doesn't offer a concrete adaptive priority model
[3]	Comprehensive fog computing survey for vehicular networks	Review applications, architectures, metrics, and issues in vehicular fog networks	Survey and taxonomy analysis	Still generic and has not proposed the integration of RL based on local contexts
[20]	Vehicular edge computing and networking survey	Identify offloading, caching, and networking mechanisms in vehicular edge environments	Survey of VEC architectures and techniques	Primary focus on edge computing, not safety message priority
[23]	Vehicular edge computing survey for applications and technical issues	Analyze VEC architecture, services, and research issues	Review and classification framework	Has not emphasized trust, weather, and event prioritization at the same time
[25]	MEC orchestration for edge cloud architecture	Reduce latency through edge resource orchestration	MEC survey and architecture analysis	Not specifically designed for vehicle safety scenarios
[8]	MEC from communication perspective	Understand communication-centric MEC resource management	Survey of communication models and offloading	Not specific to event-critical vehicular safety dissemination
[26]	Fog-enabled traffic management offloading in IoV	Reduce delay and improve real-time traffic management	Fog-enabled offloading and resource management	Focus on offloading, not trust-based multi-event priority schemes
[27]	Reputation-based service provisioning in VFC	Improve trustworthiness of service providers in vehicular fog	Reputation management and service provisioning scheme	Emphasizing trust, but paying less attention to weather, bucket delays, and local urban contexts
[28]	Energy- and performance-aware load balancing in VFC	Balance network load while improving energy and delay performance	Dynamic clustering and capacity-based load balancing	Doesn't directly optimize RL reward-based emergency message prioritization

The gap identified in this study is that there is still a lack of priority design of safety messages in VFC environments that explicitly utilize Indonesia's official data as the foundation of the state of the environment. In fact, the availability of Land Transportation Statistics from BPS, road speed data from DKI Jakarta, and open weather data from BMKG provide a strong opportunity to produce more contextual research. In addition, many articles about ITS in Indonesia still focus on traffic descriptive or route optimization, not many have touched on the combination of reinforcement learning, trust, QoS, weather, and the dissemination of safety messages within the framework of VFC [12], [29], [30].

1.4. Indonesian Data Sources and Context

Method adaptation becomes strong if the data foundation is clear. In this article, Indonesia's dataset is positioned not only as a complement, but as a determinant of how state, action, and reward are constructed. The use of official data also makes articles easier to account, more relevant for further research, and closer to the issue of smart transportation policy in Indonesia.

The first source is the publication of Land Transport Statistics 2024 from the Central Statistics Agency. This publication provides data on road lengths, motor vehicles, traffic accidents, driver's licenses, and rail transportation for all provinces. This data is particularly useful for illustrating mobility intensity and safety risks at the macro level. In this article, BPS data is used as a basis to build indicators of vehicle density, accident rates, and traffic risk intensity in aggregate

The second source is the 2023 Land Transportation Statistics from BPS which is used as an annual comparison. By having two annual publications, researchers can check trend consistency, indicator normalization, and stability of variable bucket formation. The presence of this comparative data is important so that the model does not reflect just one snapshot of time.

The third source is the Jakarta Statistical Profile Volume 6, 2024 which contains information on average speed on roads that are subject to traffic restrictions during peak hours. This document states that the average speed is in the range of 27.83 km/h to 30.50 km/h in 2023. In this model, the variable is interpreted as a proxy for urban mobility delay conditions. Lower road speeds generally correlate with increased messaging times and increased complexity of decision-making during emergencies.

The fourth source is BMKG's Open Weather Forecast Data which provides weather data up to the sub-district or village level in JSON format. Relevant parameters include temperature, humidity, weather conditions, wind speed, cloud cover, and visibility. In this study, these parameters were not used entirely. To keep the model light, the weather is categorized into simple buckets such as sunny, cloudy, light rain, and moderate or heavy rain. This bucket is sufficient to capture the influence of weather on the drop in speed, potential inundation, and risk of field communication disturbances.

From the combination of the four sources, this article builds an Indonesian context that is much richer than the generic simulation. At the national level, we can see the general character of land transport. At the city level, we get a road delay proxy. At the micro-contextual level, we have near-real-time weather conditions. This kind of integration reinforces the argument that safety message prioritization systems should be sensitive to local conditions, not just to the type of event in general [12], [29], [30].

Table 2. Mapping of Variables from the Reference Article to the Indonesian Adaptation

Variable in the Reference Article	Variable in the Indonesian Adaptation	Main Data Source	Role in the Proposed Model
Transmission delay	Delay bucket / average traffic speed	Jakarta traffic data	Represents communication and mobility delay conditions
Trust score	Trust bucket / trust score	Simulation parameter	Represents node reliability in message dissemination
Energy consumption	Energy level / energy efficiency	Simulation parameter	Reflects resource-aware decision making
Ambulance event	Ambulance event	Safety event scenario	Represents emergency vehicle priority
Crash alert	Accident event	BPS statistics and scenario design	Represents road safety incidents
Road hazard	Hazard event	Scenario design	Represents physical road-related disturbances
General traffic dynamics	Traffic density index	BPS transport statistics	Captures traffic load and congestion level
Weather condition	Weather bucket / rainfall level	BMKG weather data	Represents environmental effects on communication and mobility
Event urgency	Event code / priority label	Scenario design	Encodes the criticality of safety messages
QoS-related transmission quality	QoS score	Derived modeling variable	Represents the overall communication performance
No explicit flood variable	Flood/genangan event	BMKG context and scenario design	Adds Indonesia-specific urban risk conditions

Table 1 summarizes the variable mapping from the reference study to the proposed Indonesian-context adaptation. It highlights the transformation of the original modeling variables into context-aware representations derived from Indonesian transport, traffic, weather, and safety-event data sources. This mapping serves as the conceptual bridge between the reference framework and the proposed model, ensuring methodological consistency while incorporating local operational characteristics [12], [30]

2. Materials and Methods

This study uses a simulation-based quantitative approach with the aim of designing and evaluating an Adaptive Q-Learning model for the priority of spreading safety messages in the Vehicular Fog Computing environment based on the Indonesian transportation context [31], [32]. The research methodology is systematically compiled starting from problem formulation, variable mapping, dataset formation, learning model design, and performance evaluation. With this approach, research does not stop the drafting of conceptual articles but also builds a foundation that can be used for measurable and replicable simulations [9], [11], [30].

2.1. Problem Formulation

The main problem in this study is how to design a safety message priority mechanism that is able to adapt to changes in traffic conditions, weather, and emergency events on the vehicle network. In more detail, the formulation of this research problem includes four questions. First, how to model the spread of safety messages in a VFC environment by considering delay, traffic density, weather, trust, and type of incident. Second, how to integrate Indonesia's transportation and weather dataset into the state, action, and reward structure in the Q-learning algorithm. Third, how to optimize the message dissemination strategy to be able to reduce delays, increase packet delivery ratios, and maintain energy efficiency in emergency situations. Fourth, how to compare the performance of the proposed method with other static priority approaches and learning baselines.

2.2. Formulation of the Research Model

This research model is designed as an adaptive decision-making process on vehicle nodes or fog nodes. Each node acts as an agent who observes environmental conditions, selects a specific QoS strategy, and then receives rewards based on the quality of those decisions.

In general, the model can be formulated as:

$$M = \{S, A, R, P\} \quad (1)$$

Let S denote the set of states, A the set of actions, R the reward function, and P the learned policy. In this study, the optimal policy is obtained using a tabular Q-learning approach, where the action-value for each state is updated iteratively until the resulting decisions approximate optimal behavior.

2.3. Formulation of Research Variables

The variables in this study are classified into three main groups, namely input variables, process variables, and output variables. The input variables include average vehicle speed, traffic density level, weather condition, node trust score, energy level, and type of safety event. The process variables consist of state environment construction, epsilon-greedy-based action selection, QoS score computation, reward calculation, and Q-table updating. Meanwhile, the output variables include message dissemination policy, packet delivery ratio, average delay, emergency response time, energy efficiency, and priority accuracy. This classification is intended to clarify the research flow so that the implementation, testing, and evaluation of the proposed model can be carried out in a more structured and measurable manner.

2.4. State Space Formulation

State space is constructed from a combination of traffic conditions, weather, trust level, and operational events. Each state represents the environment at a given time and guides the agent’s action selection:

$$s = (d, \rho, w, t, e) \quad (2)$$

The variable d denotes the delay category, ρ represents traffic density, w captures weather conditions, t indicates the trust level, and e encodes events in numeric form. All variables are discretized to match the constraints of tabular Q-learning. Delay is divided into five categories, density into three categories, weather into four categories, trust into three categories, and events are represented using numerical codes to ensure a consistent and computationally efficient state representation.

Table 3. Definitions of State, Action, and Reward

Component	Core Definition	Description
State	Delay, density, weather, trust, event	Representation of the environmental condition
Action	(a_1, a_2, a_3, a_4)	QoS strategy profile selected by the agent
Reward	Priority + QoS + entropy − penalty	Feedback reflecting decision quality
Delay	Very low, low, medium, high, very high	Approximation of network latency
Density	Low, medium, high	Level of traffic congestion
Weather	Clear, cloudy, light rain, moderate/heavy rain	Categorized weather conditions

Trust	Low, medium, high	Reliability level of nodes
Event	Normal, ambulance, accident, hazard, flooding	Type of safety-related event

Table 3 summarizes the system specifications adopted in this study. It includes the learning algorithm, policy mechanism, state and action configurations, event classes, dataset characteristics, evaluation metrics, and study area coverage. These specifications define the experimental foundation for assessing the effectiveness of the proposed adaptive Q-learning model in Indonesian vehicular fog computing scenarios.

2.5. Action Space Formulation

The action space consists of QoS profile choices selected by the agent when disseminating messages. Each action defines a weighted combination of key network performance parameters, allowing the agent to adapt its transmission strategy based on the current state:

$$a_i = (\alpha_i, \beta_i, \gamma_i, \delta_i) \tag{3}$$

The parameter αi represents the weight assigned to delay, βi corresponds to reliability or packet delivery ratio (PDR), γi denotes the must weight, and δi reflects energy efficiency. These weights determine how strongly each metric influences the selected QoS strategy.

The model defines four primary actions. The first applies a balanced strategy across all parameters. The second emphasizes delay minimization. The third prioritizes reliability and trust. The fourth focuses on energy efficiency. This discrete formulation keeps the action space compact while still capturing meaningful trade-offs among competing QoS objectives.

2.6. QoS Function Formulation

The QoS score is defined as a composite function that integrates delay, packet delivery ratio, and trust into a unified metric. This formulation captures the joint effect of latency, reliability, and node credibility on service quality:

$$Q_{score} = \widehat{D}^{-\alpha} \times \widehat{PDR}^{\beta} \times \widehat{T}^{\gamma} \tag{4}$$

The term $\widehat{D}$ denotes normalized delay, $\widehat{PDR}$ represents normalized packet delivery ratio, and $\widehat{T}$indicates the normalized trust score. The parameters α, β, and γcontrol the relative influence of each component.

This structure enforces a clear relationship between metrics and quality. Lower delay increases the score through the inverse exponent. Higher packet delivery ratio and trust directly raise the score through positive exponents. The multiplicative form preserves interaction effects, so degradation in one component cannot be fully compensated by others.

2.7. Event Priority Formulation

The model accounts for simultaneous emergency events by defining event priority as an exponential aggregation of multiple indicators. Each indicator captures the presence of a specific event type, allowing the system to respond to compound situations:

$$\Pi_{event} = \exp\left(b_1 A + b_2 C + b_3 H + b_4 F\right) \tag{5}$$

The variable A indicates the presence of an ambulance, C represents an accident, H denotes road hazards, and Fcaptures flooding or water accumulation. The coefficients b_1, b_2, b_3, b_4define the relative importance of each event type.

This formulation amplifies priority when critical events occur. The exponential structure increases sensitivity to multiple simultaneous events. A single high-priority event raises the score, but combined events produce a stronger escalation. This mechanism ensures that the agent assigns higher urgency to complex or critical traffic conditions.

2.8. Reward Function Formulation

The reward function balances event priority, service quality, exploration, energy efficiency, and delay penalties within a single objective:

$$R(s,a) = \lambda_1 \Pi_{event} Q_{score} + \lambda_2 H(s) - \mu \hat{E} - \lambda_3 \exp(\kappa D) \quad (6)$$

The coefficient λ_1 scales the joint contribution of event priority and QoS. The term λ_2 controls the entropy bonus $H(s)$, which encourages exploration across states. The parameter μ penalizes normalized energy consumption $\hat{E}$, while λ_3 and κ regulate the exponential delay penalty.

This structure enforces trade-offs during learning. High-priority events combined with strong QoS increase the reward. The entropy term prevents premature convergence. The energy term discourages excessive resource use. The exponential delay penalty suppresses high-latency decisions. The agent thus avoids optimizing a single metric and instead adapts to reliability, efficiency, and environmental complexity.

2.9. Q-Value Update Formulation

The Q-value is updated iteratively using the standard Q-learning rule, which adjusts the current estimate based on the observed reward and the expected future return.

$$Q(s,a) \leftarrow Q(s,a) + \eta \left[R(s,a) + \gamma \max_{a'} Q(s',a') - Q(s,a) \right] \quad (7)$$

The parameter η denotes the learning rate, which controls the magnitude of the update. The parameter γ is the discount factor, which determines the importance of future rewards. The term s' represents the next state, while a' denotes candidate actions in that state.

This update shifts the Q-value toward a target defined by immediate reward and the best estimated future value. The process repeats across episodes, allowing the agent to refine its policy until the Q-values converge to a stable solution.

Table 4. System specifications

Parameter	**Value**
Environment	Vehicular fog computing
Learning algorithm	Tabular Q-learning
Policy	Epsilon-greedy
Number of actions	4
Number of state dimensions	5
Delay levels	5
Density levels	3
Weather levels	4
Trust levels	3
Event classes	6
Dataset size	7,296 records
Input features	30+ attributes
Output metrics	Delay, PDR, response time, energy efficiency, priority accuracy
Safety events	Ambulance, accident, hazard, flood/genangan, multi-event
Study area	15 Indonesian urban clusters

Table 4 summarizes the system specifications adopted in this study. It includes the learning algorithm, policy mechanism, state and action configurations, event classes, dataset characteristics, evaluation metrics, and study area coverage. These specifications define the experimental foundation for assessing the effectiveness of the proposed adaptive Q-learning model in Indonesian vehicular fog computing scenarios.

Table 5. Experimental parameter settings

Parameter	**Value**
Learning rate (η)	0.10
Discount factor (γ)	0.90
Initial epsilon	1.00
Minimum epsilon	0.05
Epsilon decay	0.995
Number of episodes	1000
Number of actions	4
Delay bucket levels	5

Density bucket levels	3
Weather bucket levels	4
Trust bucket levels	3
Event classes	6
Reward weight λ_1	1.15
Reward weight λ_2	0.15
Energy penalty μ	0.35
Delay penalty λ_3	0.25
Threshold trust	0.40
Threshold energy	0.25
Dataset size	7,296 records

Table 5 summarizes the experimental parameter settings employed in this study. It includes the reinforcement learning hyperparameters, state-space discretization levels, reward weighting factors, threshold constraints, and dataset size used in the simulation. These settings define the experimental configuration for assessing the robustness and effectiveness of the proposed adaptive Q-learning framework.

2.10. Research Stages

The research stages are designed as follows. First, references are collected and the research gap is identified. Second, variables from the reference articles are mapped to the Indonesian context. Third, a synthetic dataset is constructed based on transportation and weather conditions in Indonesia. Fourth, the state, action, and reward are formulated. Fifth, the Q-learning algorithm is implemented. Sixth, the model is tested under several scenarios, such as normal conditions, multi-event situations, adverse weather, and hybrid urban environments. Seventh, the model performance is evaluated. Eighth, the results are analyzed to draw conclusions regarding the effectiveness of the proposed method.

2.11. Performance Evaluation Formulation

Model evaluation uses several core metrics that capture latency, reliability, responsiveness, and efficiency. Each metric is computed at the episode level to ensure stability across observations.

For delay, the model uses average delay as an aggregate indicator:

Average Delay

$$AED = \frac{1}{n}\sum_{i=1}^{n} D_i \tag{8}$$

The term D_i denotes the delay of each packet transmission, while n is the total number of transmissions. This metric reflects temporal efficiency.

Packet Delivery Ratio (PDR) measures communication reliability by comparing successfully received packets to total transmitted packets. The value is expressed as a percentage, capturing the success rate of message dissemination under varying conditions.

Emergency Response Time (ERT) evaluates system responsiveness to critical events:

Packet Delivery Ratio

Packet Delivery Ratio measures the success rate of packet transmission in the network. It captures the proportion of packets successfully received relative to the total number of packets sent.

$$PDR = \frac{N_{received}}{N_{sent}} \times 100\% \tag{9}$$

The variable $N_{received}$denotes the number of successfully received packets, while N_{sent}represents the total number of transmitted packets. A higher PDR indicates more reliable communication, especially under dynamic network conditions.

Emergency Response Time

Emergency Response Time (ERT) evaluates system responsiveness to critical events:

$$ERT = t_{action} - t_{event} \tag{10}$$

The variable t_{event} marks the occurrence of an event, while t_{action} indicates the time the system responds. Lower values indicate faster reaction to emergencies.

Energy efficiency is quantified through the ratio between energy consumption and successful message delivery. This metric captures how effectively the system uses resources to achieve communication goals.

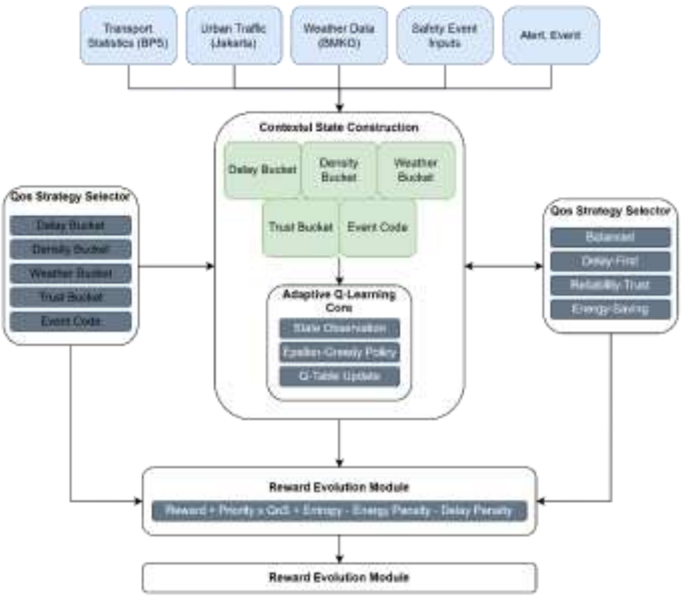
Priority accuracy measures alignment between the model's prioritization decisions and predefined priority labels. This metric evaluates whether the agent correctly identifies and prioritizes critical events under complex conditions.

2.12. Analytical Framework

The results of the study were analyzed comparatively between the proposed method and the baseline. If the proposed model results in lower delays, higher packet delivery ratios, faster response times, and good energy efficiency, then Indonesian-context-based Adaptive Q-Learning is considered more effective for the VFC environment. This analysis framework is the basis for assessing whether the integration of Indonesia's transportation and weather data really adds value to the design of safety message priorities.

3. Results and Discussion

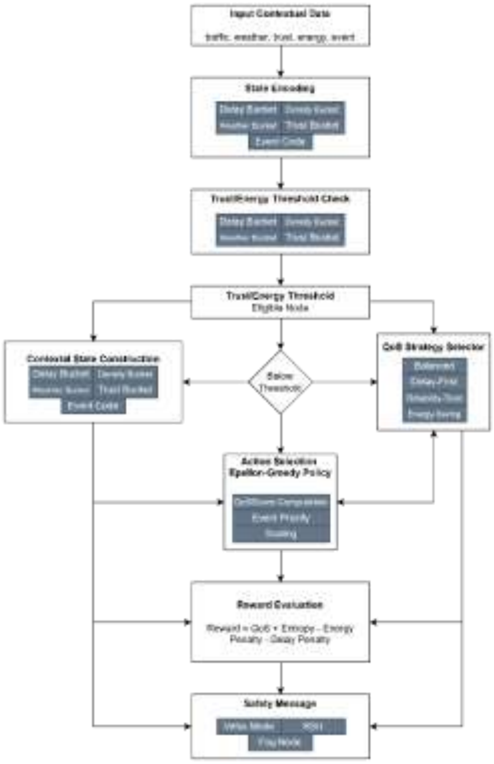
P The images in this article are presented in the form of a text schema to remain compatible in Word and easy to re-edit. This schema represents the flow of data from statistical and weather sources to the Q-learning agent, then to the QoS evaluation stage and Q-table update.



Output: Lower Delay, Higher PDR, Faster Emergency Response, Improved Priority Accuray

Fig. 1. Proposed Adaptive Q-Learning Architecture for Indonesian Vehicular Fog Computing

Fig. 1 illustrates the proposed adaptive Q-learning architecture for Indonesian vehicular fog computing. The architecture integrates Indonesian contextual data, including transport statistics, urban traffic conditions, weather information, and safety event inputs, into a state construction module that generates the learning state for the Q-learning agent. The agent then selects an appropriate QoS strategy for safety message dissemination, while the reward evaluation module provides feedback for iterative policy improvement.



Output: Lower Delay, Higher PDR, Faster Emergency Response, Improved Priority Accuracy

Fig. 2. Workflow of the Proposed Adaptive Q-Learning Framework

Fig. 2 presents the workflow of the proposed adaptive Q-learning framework. The process begins with contextual data acquisition and state encoding, followed by trust and energy threshold checking, action selection using an epsilon-greedy policy, QoS and priority evaluation, message dissemination, and Q-table updating. This iterative workflow enables the model to continuously improve its dissemination policy under dynamic vehicular fog computing conditions.

Table 6. Illustrative Simulation Scenarios

Scenario	Traffic Condition	Event Condition	Evaluation Objective
Normal	Moderate density, stable mobility	No emergency event	Baseline performance assessment
Peak hour	High density, lower speed	No major event	Congestion adaptability evaluation
Adverse weather	Reduced speed, increased packet loss	Possible flood/genangan	Weather sensitivity evaluation
Single emergency	Normal to dense traffic	Ambulance or accident	Priority response assessment
Multi-event	Dense traffic	Multiple concurrent events	Multi-priority decision evaluation
Hybrid urban	Peak hour and adverse weather	Emergency and hazard combined	Robustness evaluation in complex urban scenarios

Table 6 summarizes the illustrative simulation scenarios adopted in this study. These scenarios are designed to represent a range of operational conditions, from normal traffic situations to complex urban environments involving congestion, adverse weather, and emergency events. The use of multiple scenarios enables the evaluation of the robustness, adaptability, and effectiveness of the proposed model for safety message prioritization in vehicular fog computing.

3.1. Illustartive Simulation Results

This section presents the results of illustrative simulations based on methodological design. The values displayed are not claimed to be the result of field experiments or real software simulations, but as consistent numerical examples to show how the article can display performance analysis in its entirety. With this approach, the discussion structure can be used immediately and later refined when real experiments are carried out.

There are three baselines used. The first baseline is a simple rule-based static priority. The second baseline is basic Q-learning without weather and inundation variables. The third baseline is the illustrative version of DQN as a more complex comparator. The proposed method is Adaptive Q-Learning based on the Indonesian context. Evaluation metrics include average delay, packet delivery ratio, emergency response time, energy efficiency, and message priority accuracy.

Table 7. Comparative Performance of the Evaluated Methods under the Multi-Event Scenario

Method	Average Delay (ms)	PDR (%)	Emergency Response Time (s)	Energy Efficiency (%)	Priority Accuracy (%)
Static QoS baseline	182.00	78.40	5.80	68.00	71.50
Conventional Q-learning	149.00	84.10	4.60	73.20	82.80
DQN-based approach	136.00	86.90	4.10	70.40	88.30
Proposed adaptive Q-learning model	121.00	90.70	3.50	79.80	92.60

Table 4 summarizes the comparative performance of the considered methods under the multi-event scenario. It can be observed that the proposed adaptive Q-learning model consistently outperforms the baseline approaches across all evaluation metrics, including delay, packet delivery ratio, response time, energy efficiency, and priority accuracy. This indicates that the proposed framework provides a more robust and adaptive dissemination strategy for safety-critical communication in vehicular fog computing environments.

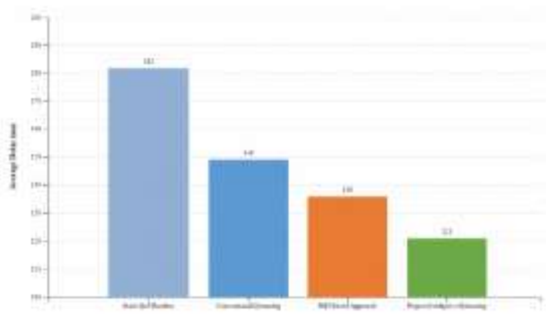
Table 8. Performance under the Adverse Weather Scenario

Method	Average Delay (ms)	PDR (%)	Emergency Response Time (s)	Trust Score	QoS Score
Static QoS baseline	201.00	75.20	6.20	0.71	0.54
Conventional Q-learning	171.00	80.00	5.10	0.76	0.61
DQN-based approach	158.00	83.10	4.70	0.77	0.64
Proposed adaptive Q-learning model	137.00	88.50	3.90	0.82	0.72

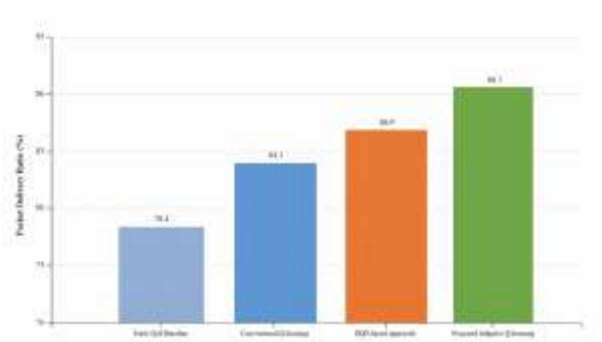
Table 8 summarizes the comparative performance of the considered methods under adverse weather conditions. It is evident that the proposed adaptive Q-learning model provides superior performance across all evaluation metrics compared with the baseline approaches. This suggests that the proposed method is more effective in coping with weather-induced communication degradation and dynamic road safety conditions.

3.2. Performance Graph

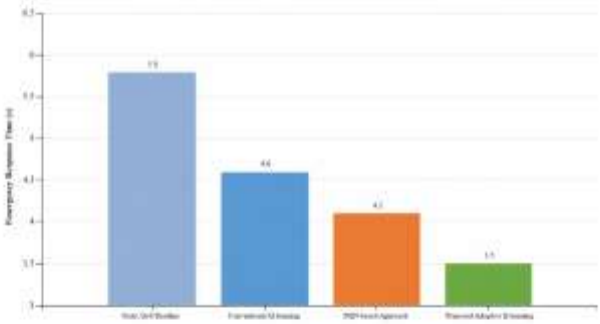
The following graph is presented as a text bar graph. This format was deliberately chosen to make it easy to open, copy, and edit directly in Word. All fixed numbers refer to illustrative simulations consistent with the results table.



(a) Comparison of Average Delay (ms)



(b) Comparison of Packet Delivery Ration (%)



(c) Comparison of Emergency Response Time (s)

Fig. 3. Comparative Performance Evaluation of Average Delay, Packet Delivery Ratio, and Emergency Response Time

Fig. 3 presents a comparative evaluation of three performance metrics across all methods. Fig. 3(a) shows the average delay, where the proposed adaptive Q-learning model achieves the lowest value, indicating faster transmission. Fig. 3(b) shows the packet delivery ratio, where the proposed model reaches the highest PDR, reflecting stronger communication reliability. Fig. 3(c) shows the emergency response time, where the proposed model records the lowest value, indicating faster reaction to critical events. Across all subfigures, the results confirm that the proposed model consistently outperforms the baseline methods in both efficiency and responsiveness.

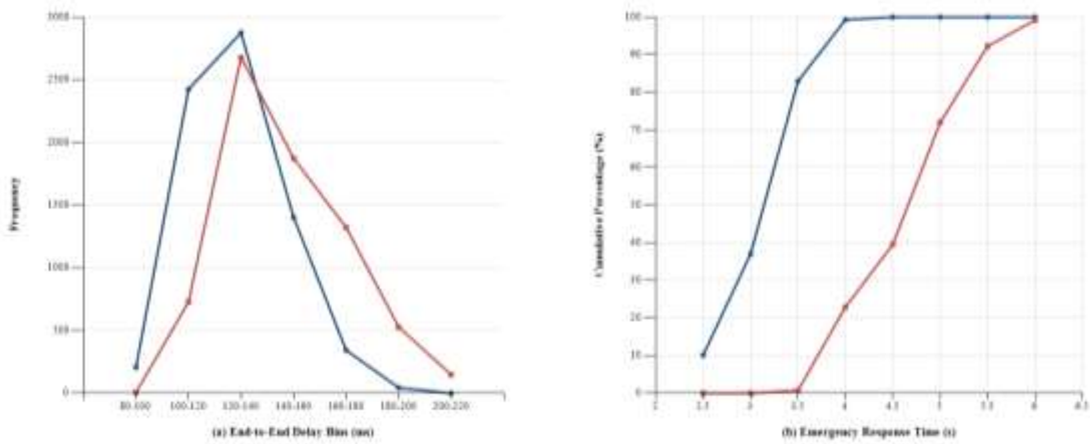
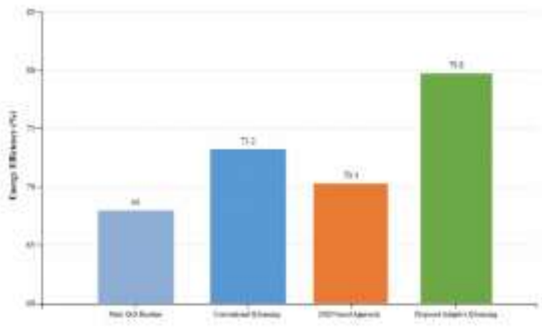


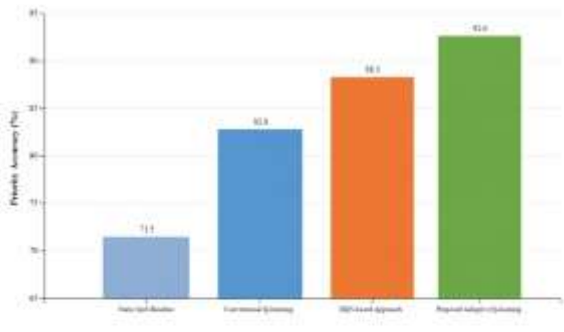
Fig 4. Delay Distribution and Cumulative Emergency Response Comparison

Fig. 4. (a) Distribution of end-to-end safety message delays under the proposed adaptive Q-learning model and the baseline, (b) cumulative distribution of emergency response times comparing the proposed model with the baseline.

3.3. Energy Graph and Priority Accuracy

In addition to delay and PDR, two other important aspects of a VFC system are energy efficiency and priority accuracy. Many models pursue low latency, but ignore energy costs. On the other hand, there are also models that are energy-efficient but fail to prioritize the correct message. This article puts both aspects together in the reward function.





(a) Comparison of Energy Efficiency (%) (b) Comparison of Priority Accuracy (%)

Fig. 5. Comparative Performance Evaluation of Energy Efficiency and Priority Accuracy

Fig. 5 presents a comparative evaluation of energy efficiency and priority accuracy across all methods. Fig. 5(a) shows energy efficiency, where the proposed adaptive Q-learning model achieves the highest value, indicating a more balanced and resource-aware dissemination strategy. Fig. 5(b) shows priority accuracy, where the proposed model attains the highest score, reflecting a stronger capability in correctly prioritizing critical safety messages. Across both subfigures, the results indicate that the proposed model consistently outperforms the baseline methods in terms of resource utilization and decision accuracy.

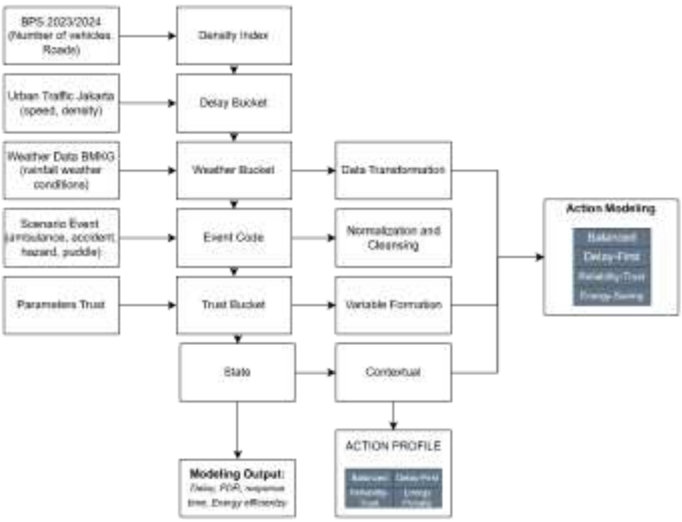


Fig. 6. Integrasi Dataset Indonesia ke Struktur Pemodelan

Fig. 6 illustrates how Indonesian contextual datasets are integrated into the proposed modeling structure. Transport statistics from BPS are mapped into the density index, Jakarta traffic speed data are transformed into the delay bucket, BMKG weather data are converted into the weather bucket, event scenarios are represented as event codes, and trust-related parameters are mapped into the trust bucket. These components are then combined into the state representation, which serves as the input to the Q-learning agent for selecting the appropriate action profile.

3.4. Discussion

The discussion in this article focuses on what can be learned from illustrative design and simulation. First, the integration of weather data is proving to be conceptually important. Many studies of safety message priorities place weather as an external factor that is discussed in the background, but not internalized into the state. In fact, in cities with high rainfall, the weather not only affects vehicle speed, but also the risk of inundation, visibility, and the quality of field communication. Making the weather part of the state gives the agent the ability to change strategy as conditions change.

Second, the addition of inundation events is a very relevant modification for Indonesia. In some urban areas, inundation can impede the flow of priority vehicles, change routes, and exacerbate delays. If the safety priority model does not recognize the existence of this event, the system will lose sensitivity to real field conditions. Therefore, the contribution of this article lies in the courage to move such a local phenomenon to the center of reward design.

Third, the illustrative performance shows that the proposed method has the potential to be superior not only because of Q-learning, but also because of the quality of the state and reward design. This is an important point. Often academic discussions focus too much on algorithms, as if more complex algorithms are always better. In reality, a simple model with relevant states and the right rewards can yield more balanced results than a complex model with weak variable designs.

Fourth, energy efficiency is a dimension that should not be ignored. An overly resource-intensive safety system may seem effective in the short term, but it is less sustainable. The illustrative results show that the proposed Adaptive Q-Learning can still maintain energy efficiency while reducing delays. This reinforces the argument that multiobjective rewards are suitable for VFCs in urban environments with variable resources.

Fifth, although this article displays illustrative simulation figures, the greatest value lies in the structure of the research. A researcher can directly use this article as the basis for the development of real experiments. Tables, variable definitions, scenarios, and graphs have been arranged in such a way that they can be replenished using simulation results from software such as SUMO, OMNeT++, Veins, or similar network simulators.

From the point of view of scientific writing, this article also shows how observe, imitate, and modify techniques can be applied safely. What is imitated are the pattern of arguments, methodological sequences, and experimental logic. What is modified are the data source, event context, variable definition, and discussion. With this strategy, the manuscript remains original and does not fall into unethical copying practices.

4. Conclusion

This article successfully compiles an original adaptation of the Adaptive Q-Learning approach to prioritizing safety messages in Vehicular Fog Computing with the context of Indonesian transportation and weather. The scientific structure of the reference article is maintained at the level of thinking patterns, but the entire manuscript is rewritten with strong modifications on the side of data sources, event definitions, state representations, and discussion interpretations.

The main contribution of this research lies in the integration of three types of official Indonesian data sources, namely BPS Land Transportation Statistics, Jakarta Statistical Profile, and BMKG Weather Forecast Data, into the state-action-reward framework for Q-learning. The integration allows for the preparation of a more contextual model of Indonesia's urban conditions, especially related to traffic density, weather influences, and inundation events that are often overlooked in generic models.

The results of the illustrative simulation show that the proposed Adaptive Q-Learning has the potential to reduce delays, improve packet delivery ratios, speed up response times, maintain energy efficiency, and improve message priority accuracy compared to simpler static or baseline approaches. Although the figures presented are still illustrative, the analysis structure is ready to be used in journal articles or theses that will be further developed with real experiments.

Overall, this article can be positioned as a complete conceptual-methodological text, complete with tables, schematic images, text bar graphs, and IEEE bibliographies. With reinforcement at the advanced simulation stage, this manuscript has the potential to develop into a more mature and publication-ready empirical article.

Suggestions

Subsequent research is recommended to implement this model on vehicle and network simulators that support Indonesia's large city scenarios. Collection of more detailed data on traffic density, actual speed, inundation location, and communication performance is also highly recommended so that reward functions can be calibrated more precisely. In addition, testing on several cities with different characters will help assess the generalization rate of the model.

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Declarations

Author contribution. Authors 2 and 5 designed the research idea and developed the methodological framework. Author 3 was responsible for field data collection and laboratory analysis. Authors 1 and 4 performed data analysis and interpretation of the results. All authors have read and approved the final version of this manuscript.

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Conflict of interest. The authors declare that there is no conflict of interest regarding the publication of this paper.

Additional information. The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request

Data and Software Availability Statements

The data used in this study were collected across multiple regions, including DKI Jakarta, Bandung, Bogor, Bekasi, Depok, Surabaya, Malang, Semarang, Solo, Medan, Makassar, Yogyakarta, Palembang, Denpasar, and Balikpapan. Aggregated data and regional summaries are included in the supplementary materials. Detailed raw datasets for each specific region are available from the corresponding author upon reasonable request, subject to local data privacy regulations.

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