

An Intelligent Quality of Service Architecture for Information-Centric Vehicular Networking

Cutifa Safitri, Yoshihide Yamada, Sabariah Baharun, Shidrokh Goudarzi, Quang Ngoc Nguyen, Takuro Sato

Abstract— Information-Centric Vehicular Networking (ICVN) is a paradigm shift in vehicular communication which implements self-content management to eliminate issues related to the current host-based IP network. Due to the exponential growth in demands of multimedia services, current vehicular networks face several challenges to support mobility with optimal Quality of Service (QoS). To achieve the high QoS performance, an intelligent vehicular network service with dynamic control mechanisms is necessary. This motivates the development of dynamic content management that implements an intelligence architecture. The proposed intelligent architecture comprised of two primary stages: classifications and discovery. In the first stage, a classifier system categorizes the user's content request and the second stage presents an adaptive forwarding path discovery towards the nearest content provider. Here, a Rule-based Evolutionary Systems (RES) agent performs exploration and exploitation to discover every possible forwarding path in the heterogeneous network. The agent then performs the discovery action that is guided by the variance introduced in the Reinforcement Learning (RL) policy. The simulation results confirm the suitability and scalability of the proposed architecture, particularly in reducing data packet delivery time, increasing data transfer rate, improve interest success rate, and lower the network traffic by 70%, 28%, 24% and 65% respectively.

Index Terms— Artificial Intelligent, Information-Centric Networking, Quality of Service, Reinforcement Learning, Vehicular Network.

I. INTRODUCTION

INFORMATION-CENTRIC Vehicular Networking (ICVN) is an emerging branch of Information-Centric Networking (ICN) that implements the naming scheme for content forwarding and promotes content as the first-class entities [1]. This communication paradigm shift is desirable to meet the expected exponential growth in the number of content exchanges by 2020. ICN loosens the required binding between

content requesters and content providers. Thus, ICN provides the build-in mobility management support, without relying on an additional infrastructure [2]. This principle makes ICVN be one potential candidate for the mobile communication and vehicular networks.

In the next network generation, one of the most desirable features is the ability to achieve seamless mobility over the various network infrastructure. Current vehicular technology can support many wireless interfaces, such as ad-hoc, Wi-Fi, and WiMAX. ICN architecture enables a new strategy layer which takes advantage of multiple simultaneous connections. Figure 1 depicts the ICN protocol stacks compared with the existing technique. This feature is designed to support mobility by exploiting multiple connections under the dynamically changing conditions. Thus, a vehicle network (VANET) may communicate by choosing the best interface according to the applications need.

In principle, the VANET is a harsh environment which requires high-speed and real-time communication links with various Quality of Service (QoS) demands. Speeding users may need to perform frequent handoffs and continuously request services from different Point of Attachments (PoAs). This nature incurs higher network load and traffic because the users need to retransmit data packets towards their new PoAs. Another challenge arises due to the unique traffic generation patterns and delivery requirements for the specific type of application. Such as, real-time and conversation-based contents are sensitive to both network delay and throughput, which are the key metrics that determine user QoS performance.

These challenges motivate the proposal of intelligent ICVN architecture in this study. A recent study shows the benefits of Artificial Intelligent (AI) implementation for the realization of intelligent management and communication networks services [3]. Mobile communication and vehicular network need intelligent decisions to manage multiple resources and dynamic traffic exchanges. Towards this, our study aims to develop an AI based ICN system with dynamic content management to facilitate mobile QoS in the mobile environment, especially for the case of high speed mobility. The first contribution is by maximizing the data transfer and interest success rate through the classification of the incoming request based on the proposed content QoS and cost estimation. Second, the proposal lowers the network load and delay by implementing an AI based route exploration towards destination nodes that are suitable for mobile communication.

Manuscript received April 30, 2018. This work was supported by Japan-Asean Integration Fund (JAIF) Scholarship and Communication Systems and Networks (CSN) Research Laboratory of Malaysia-Japan International Institute of Technology (MJIT), Universiti Teknologi Malaysia (UTM).

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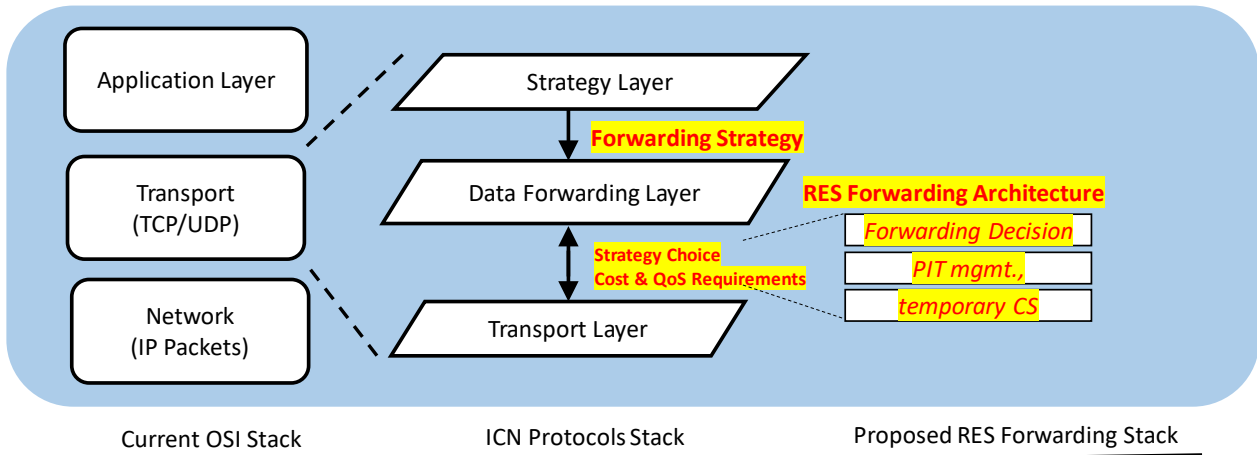


Fig. 1. The Current State of OSI Compared to ICN Protocol Stack with the Proposed RES Forwarding Stack

II. RELATED WORK

A. Reinforcement Learning Techniques

In Reinforcement Learning (RL), an agent performs learning phase by interacting with its surrounding environment directly and recording the reward it gets along the way. The goal of an RL agent is to identify the actions that will lead to the maximum cumulative future reward. Since the RL agent learns directly from its environment, it does not require vast amounts of pre-existing training data. Instead, it gradually generates training data by interacting with its environment and learning from its experience. This approach enables RL to serve as a general-purpose learning algorithm.

RL agents seek for optimal decisions that bring highest benefit in the long term, even if it may return undesirable actions in the short-term period. In other words, it is beneficial to initially forward a packet at a random interface to gain an initial hop value information. This strategy enables a better chance of yielding a positive return in the long run.

A Markov Decision Process (MDP) represents RL problems as a network with states that describe where all the nodes in the network area locate, and action represents the path to possible hops based on the position of nodes in the area. RL agents then operate in an environment described by MDP and seek to optimize their decisions by determining which action in any given state that yields the most cumulative future reward.

B. Reinforcement Learning in Information-Centric Networking

In ICN, the user can get content by sending the Interest packet as content request with content name, and the network will autonomously find suitable nearby nodes that hold the requested Data Packet to serve user request. This mechanism enables finer optimization of content delivery, which results in a reduction of network congestion and shorter response time [4].

ICN forwarding engine comprises of three main data structures as follows. The Content Store (CS), which is the in-network cache storage of content packet. The Pending Interest Table (PIT), stores the pending incoming request and its ingress face. The Forwarding Interest Base (FIB), which stores

the forwarding egress face towards the potential content provider. If an Interest packet arrives, and CS fails to satisfy, the NDN forwarding engine checks the FIB index to find the nodes with original content or a valid replica of the requested content. Then the Interest packet is forwarded through any egress face that moves it closer to the location [5].

In [6], the AI-based architecture is applied to discover temporary copies of content items that are not addressed in routing tables. The learning algorithm calculates the delay for all the interfaces after exploring chunks of a content object. The simulation result concludes that the proposal can detect and react to dynamic item availability. The implemented scenario did not consider the user mobility movement.

Study in [7] attempt to utilize RL- based solution for addressing content forwarding problem called Multi-Armed Bandits Strategy (MABS). MABS finds the set of interfaces that have a high probability to retrieve the requested content with less retrieval time. The idea is to use probabilistic explorations and content retrieval time samples for continual learning. The system needs to try each face several times, to figure out which face has a high forwarding probability to maximizes the results along the way.

Work in [8] investigate an intelligent content discovery system using deep exponential network algorithms. The proposal applies the Restricted Boltzmann Machine (RBM) based model to provide shortcut paths to access the desired content located nearest to the user. The approach analyzes the similarity comparison of topic vector extraction and cached content announcement. The results observe improvements in the cache utilization, latency, as well as low control traffic compared to other algorithms.

Study in [9] perform supervised learning for RIB and PIT using Multi-Layer Perceptron (MLP) inside the control plane. The algorithms are trained to match the content names with the egress faces listed at RIB and PIT which results as Artificial Neural Network (ANN)-FIBs. The ANN-FIBs training process is offline and identified inside the control plane; then the output is periodically copied into the data plane to substitute the default FIBs. This modification achieves better accuracy, speed, and size compared with traditional FIB.

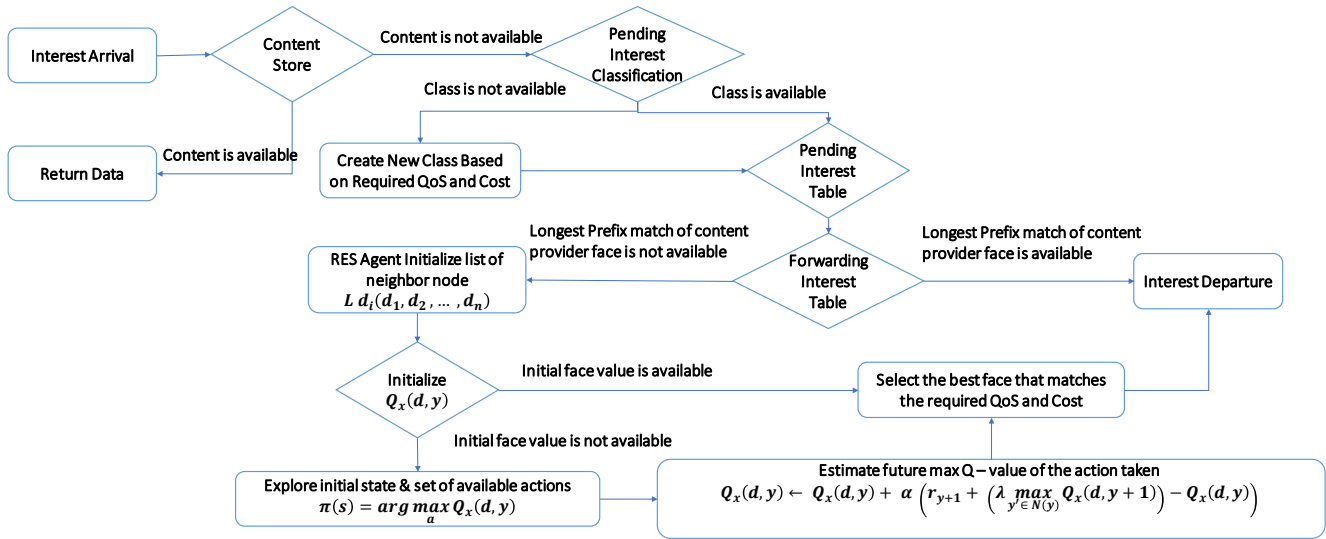


Fig. 2. The Flowchart of Proposed Rule-Based Evolutionary System (RES) Architecture for ICVN

III. THE PROPOSAL OF RULE-BASED EVOLUTIONARY SYSTEM (RES) ARCHITECTURE FOR ICVN

A. The PIT Intelligent Classification

This section discusses the proposed architecture to optimize dynamic content delivery in a mobile environment. Our architecture extends the Interest and Data packet processing mechanism of the widely used ICN platform, Name Data Networking (NDN). The fully functional ICN mechanism with detailed protocol and forwarding algorithms shown in Figure 2.

Every ICN node in the proposed ICVN system employs Pending Interest Table (PIT) which lists all of the legitimate pending request entries that unsatisfied by the content store. Each of these requests has different QoS requirement and forwarding cost to meet the request ideal end-to-end communication requirement. As the PIT queries all the pending requests, the list will eventually grow longer. Given the limited memory, the PIT needs an efficient mechanism to manage the pending interest queries to avoid memory over-utilization.

Our proposed architecture initiates the classification procedure for each of the pending requests. This classification is modeled to assign each PIT entries to an appropriate queue group according to the request's QoS and cost requirement. If there is no matching classification type for the incoming request, one new group type will be created dynamically. The PIT classification aims to ensure the continuous content delivery service by treating each request based on its required QoS communication model. Pseudocode of the classification procedure is depicted in the pseudocode in Table 1.

B. The FIB Intelligent Forwarding Strategy

This section describes the next stage of our proposed architecture which is the intelligent forwarding path discovery to route the content request closer to the content provider. As mobile users may express request for new or fresh content that is not widely available, an adaptive establishment of new forwarding path is necessary. Otherwise, the requests could get strayed, expired, and finally discarded. To realize QoS

TABLE I
PSEUDOCODE OF PIT CLASSIFICATION

IF requested data is presented in the cache THEN
Forward data packet through the best forwarding face
ELSE
IF request is presented in the PIT THEN
add interface F to the list of requesting face
ELSE
Create a new entry in the PIT
IF the new PIT entry matches from the list of existing classification THEN
Register the new PIT entry to the matched classification
ELSE
Generate a new classification (class) to best fitted for the new PIT entry
BEGIN
Select the PIT entry for New Class reproduction
Create offspring's by crossing the entry
Eventually mutate individuals
Compute new generations of Class
END
END IF
END IF
END IF

optimization of the vehicular network, this study proposes an ICN extended architecture that implements Rule-based Evolutionary System (RES). The RES forwarding is a Reinforcement Learning (RL) systems that use Genetic Algorithms (GA) to evolve the state-action value representation.

In RES forwarding, the RL component controls the agent interaction with the environment, and the GA evolutionary component evolves the problem representation. The GA can search for new adapted plausible classifiers or rewards by combining good rewards to produce new ones. Thus, the learning mechanism interacts not only with the environment but also within itself. The GA component relies on the appropriate evaluation measured from the RL component and vice versa; whereas the RL component relies on the proper classifier structure generated by the GA component to estimate the future RL value accurately. Our previous work [10], stated and clarified the strong benefit of integrating RL and GA features in the ICN implementation.

The integrated RES-based intelligent agent with the FIB will pursue an efficient exploration and exploitation of the best face to find the nearest ICN node that stores the desired content chunks. To model the representation of an RL problem, a set of 4-tuple Markov Decision Process (MDP) is defined as $\{S, A, P, R\}$, where S is the set of states with the transition from state m to another state n , A is set of actions a with $(a \in A)$, and the action a is defined by the probability $P(m, n, a)$, with corresponding reward $R(m, n, a)$ of the action.

The main task of an RL system is to learn an optimal interaction policy that interacts with an MDP problem. The policy is responsible for making the decision for the action to be taken in a given state. To solve MDP problems, we implement Q-learning optimization policy, with the premise that the best policy is the one that selects the action with the highest total future reward value, which can be mathematically expressed as:

$$\pi(s) = \arg Q_x(s, a) \quad (1)$$

Equation (1) means that policy π for a given state s always selects the action a so that the decision maximizes the Q-value. In Q-learning, the $Q(s, a)$ value of the Q-function for each state is updated iteratively at the Q-table based on the new rewards it receives.

We implement the function of Q-value for each origin node x and denoted it as $Q_x(d, y)$ to reflect the cumulative reward for reaching destination node d that stores the desired content c when routing through the intermediate hop y , as equation (2)

$$Q_x(d, y) \leftarrow Q_x(d, y) + \alpha \left(r_{y+1} + \left(\lambda \max_{y' \in N(y)} Q_x(d, y' + 1) \right) - Q_x(d, y) \right) \quad (2)$$

where the notation and meaning are summarizes at Table II.

We propose the RL based forwarding strategy as defined in the Table III to achieve the dynamic RES forwarding, implemented at each ICN node. In here, the Q-learning act as an online distance-learning mechanism towards a rewarding source, in which the Q-value indicates worthiness/value for performing an action in a given state. As routing a content request, the Q-table is consulted to decide which neighbor node y has the highest probability to serve request to destination node d faster. Note that, Q-values do not account for any prior knowledge of the initialization process.

When an Interest packet for a specific content c arrives for the first time, the node x randomizes one of its interfaces, except the interface where the packet comes from. This phase is known as initialization. After this phase, the randomized interface obtains its initial Q-value as of the first state-action taken. Therefore, when the nodes receive a similar interest packet, it will return the current best-known face to forward the Interest-packet, based on the Q-value listed by the Q-table.

Generally, an exploration policy is needs to find all optimal routes and complete the Q-table, such as by randomly selecting interface which is not currently supposed to provide the highest reward. Hence, with probability ϵ , the node will forward the packet to a different random interface with uniform distribution. The newly discovered Q-value is then compared with the current highest identified reward. This approach may exploit more knowledge for content request retrieval.

TABLE II
KEY NOTATIONS

Notation	Meaning
α	Learning rate, which is a number between 0 and 1. A high value of α means that new information will more quickly override old information.
λ	The discount rate which determines how much future rewards are worth. The higher the discount rate, the less critical the future rewards are.
$N(y)$	the set of immediate neighbors of node y
r_{y+1}	the reward earned when transitioning from node y to the next node $(y + 1)$ from set of neighbors $N(y)$
$\max_a Q_x(s, a)$	the value of the action that is estimated to return the largest (maximum) total future reward, based on all the possible actions that can be made in the next state.

TABLE III
PSEUDOCODE OF RL FORWARDING STRATEGY PROCESS

```

Input : List of available nodes  $d$  that contains content  $c$ ,
          $L d_i(d_1, d_2, \dots, d_n)$ 
Process: Q-value computation from current location  $x$  to reach  $Ld_i$ 
Output: Optimal path to destination  $d$  node that stores the requested
         content  $c$ 

Initialize Q action-value function
Initialize Q target action-value function

With probability  $\epsilon$ , select a random action  $a$ 
rand_value = randomize  $a$  value within the range of (0,1)
IF rand_value > (1.0 - exploration_threshold)
    RETURN random action for the current state
ELSE //explore initial state & set of all available actions
    FOR each action  $a \in$  set of actions  $A$  DO
        Calculate Q-value  $[s][a]$  at current position
        IF Q-value  $[s][a]$  at current position > best position
            SET best position = Q-value  $[s][a]$  at current position;
        END IF
    END FOR
END IF
RETURN ACTION

// Generate the next state using MDP transition probability
FOR each state  $s \in$  set of state  $S$  DO
    cum_value = cum_value + prob[state][action];
    IF (cum_value > best_value)
        SET best_value = cum_value
    ENDIF
END FOR
RETURN STATE

// Estimate future MAX Q-value based on available state-action values
For every available action on the current state
Estimate the probability value for all the available actions
Choose the action that yields the biggest reward for that particular state
FOR  $a=0$  to max ACTION DO
    IF (Q-value  $[s][a] < Q\text{-value}[s][a+1]$ )
        SET best_action = future action+1
    ENDIF
ENDFOR
RETURN (Q-values[state][best_action]);

// Function: Update Q-value of the current action-state
IF the new Q value is higher than the previous value
    DO update the max Q-value
        Q-value $[s][a] = Q\text{-value}[s][a] + \alpha * (\text{reward}[s+1] + (\lambda * Q\text{-value}[s+1][a]) - Q\text{-value}[s][a]);$ 
    END IF

```

IV. SIMULATIONS AND RESULTS ANALYSIS

We use ndnSIM 2.3 to evaluate the performance of the RES forwarding strategy proposal and compare with conventional NDN Best Route (BR) and Multicast (MC) forwarding scheme. The network topology is modeled as grid $G(l,n)$ where l is the number of levels in the grid network, and n is the number of nodes located at each grid level. We denote s as the number of content servers in the network and e as the nodes located at the network border that acts as edge nodes. We supposed these edge nodes are the initial user's Point of Attachment (PoA) that accommodates and facilitates the mobile user handoff via re-attachment points.

For the evaluation, we take $l=10$, $n=10$, $s=1$, and $e=10$. We further assume that every node is equipped with a cache size of 1024, implements a Least Recently Used (LRU) replacement policy. For each simulation, we place the mobile user positions randomly with the warm-up cache period between 3-5 seconds. The learning rate is set to $\eta=0.7$, with the duration of the exploration phase is 5 seconds, and the total duration of the simulation is 60 seconds. Mobile users generate content requests with an arrival rate of $\lambda=10$ request per second. We define a catalog of 110 content items (i.e., prefix files) in which a Zipf distribution with $u=1$ characterizes content popularity model.

The simulation scenario aims to mimic the practical content exchanges in a dynamic environment where the FIB is not always aware all of the content providers. In total, there are two types of Interest packet exchanged in the modeled environment. The first type of Interest request is for a popular content with the FIB configuration already saturated in the network. The second Interest request is for a fresh content that needs to be served by dynamic content providers which its existence is activated based on user request. Thus, fresh

content objects are accessible only from a randomly selected provider node, with the forwarding information absent from the FIB.

Initially, mobile users send Interest packets as content requests to the nearby edge node; which then performs subsequent ICN forwarding procedure. If the forwarding face towards a potential content provider is not addressed in the FIB table, the RES forwarding strategy is triggered. The RES agent is then presented with a list of available connected neighbor nodes, from which the agent will learn the best action to forward the interest according to the best face at current state. We implement a finite MDP which is a stochastic process with a countable number of states and actions. Due to the agent unawareness of which specific nodes that can serve the fresh content, all nodes in the vicinity area are treated to have the same probability for serving the dynamic content. The following metrics are evaluated:

- 1) The Data packet delivery time (delay), which represents the elapsing time since user sent an Interest packet, until the reception of the corresponding Data packet;
- 2) The Data rate (throughput), which defined as the average number of Data packets transmitted via the network in the one-time unit.
- 3) The Interest success rate level, which represents the total number of the satisfied Interest packets.
- 4) The network resource utilization, which represents the traffic and network resource utilized to perform the content discovery process.

Figure 3(a) shows the average Data packet delivery time against user mobility speed during Interest forwarding process. Initially, the RES has comparable performance as BR. However, it is observed that the delivery time of BR and MC is

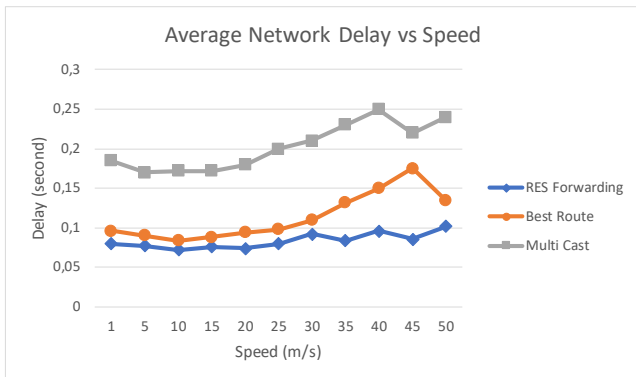


Figure 3(a) Performance comparison of Average Network Delay vs Speed

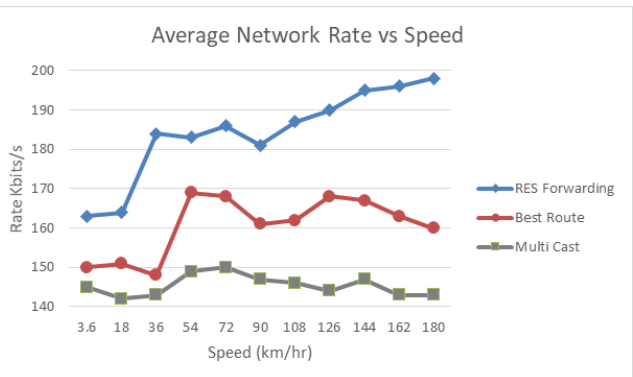


Figure 3(b) Performance comparison of Average Network Rate vs Speed

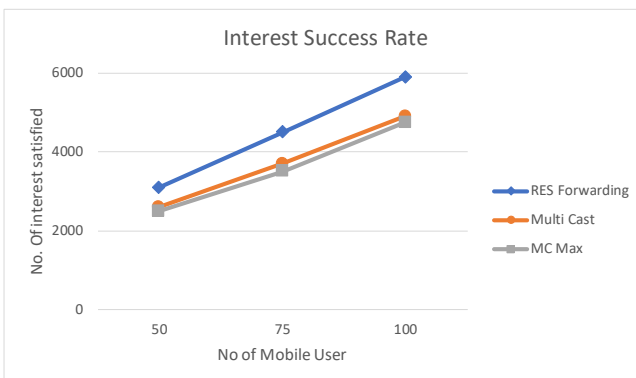


Figure 3(c) Performance of Interest Success Rate

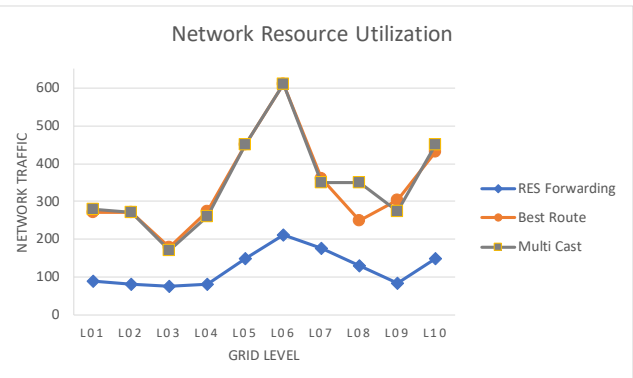


Figure 3(d) Performance Comparison of Network Resource Utilization

increasing as the user moves quicker. Whereas, the proposed RES strategy outperforms the other two strategies with an improvement up to 70%.

Figure 3(b) reports the NDN data throughput rate as the content delivery rate from provider to mobile nodes. As the speed of mobile nodes increases, the mobile user performs hand off more frequently. These events are reflected in the incline and decline presented by RES data rate. Nevertheless, the simulation results show that the proposed RES Forwarding strategy is still able to maintain data rate up to 28% higher than the BR and MC forwarding scheme.

Figure 3(c) shows the number of Interest success rate, which reflects the amount of Interest satisfied before hitting the expired time. The result shows that the proposed RES technique achieves 24% higher rate of successfully satisfied Interest. This suggests that RES can provide a more reliable mechanism and able to satisfy request within its allocated time, especially when dealing with QoS sensitive contents.

Figure 3(d) depicts the number of outgoing traffic generated until the requested Data packet found. The Interest packet is forwarded to several nodes until reaching the upstream content providers. Thus, higher outgoing traffic means that a large number of Interest packets sent as an additional attempt to explore more nodes that may store the requested content. The evaluation results show that the proposed RES forwarding generates 65% lesser traffic, suggesting its scalability compared to other relevant forwarding techniques.

V. CONCLUSION

Our proposal extends the ICN Interest packet processing mechanism by implementing AI for dynamic content management in the fast moving vehicular environment-based solution (ICVN). The proposal develops an adaptive intelligent architecture for ICVN to improve mobile QoS in a large scale with high number of users. Given that improving QoS performance needs to address multiple QoS of content types and content streams. We propose an intelligent architecture in ICVN that outperforms the currently existing solutions via classification and efficient content discovery process. The presented Reinforcement Learning agents make the feasible VANET implementation in ICN through of dynamic classifications and content forwarding mechanism within ICVN nodes. The evaluation results shows that, to optimize the end-user QoS performance, we achieve lower delivery time, higher data transfer rate and successful delivery rate, as well as lower network costs with the reductions of a network load of outgoing Data packets.

ACKNOWLEDGMENT

Acknowledgments: The authors are grateful to the Japan-ASEAN Integration Fund (JAIF) Scholarship for their financial support and to the Communication Systems and Networks (CSN) Research Laboratory of Malaysia-Japan International Institute of Technology (MJIIT), Universiti Teknologi Malaysia (UTM).

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