

# Semantic Reasoning in Cognitive Networks for Heterogeneous Wireless Mesh Systems

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**Abstract**—The next generation of wireless networks is expected to provide not only higher bandwidths anywhere and at any time but also ubiquitous communication using different network types. However, several important issues including routing, self-configuration, device management, and context awareness have to be considered before this vision becomes reality. This paper proposes a novel cognitive network framework for heterogeneous wireless mesh systems to abstract the network control system from the infrastructure by introducing a layer that separates the management of different radio access networks from the data transmission. This approach simplifies the process of managing and optimizing the networks by using extendable smart middleware that automatically manages, configures, and optimizes the network performance. The proposed cognitive network framework, called FuzzOnto, is based on a novel approach that employs ontologies and fuzzy reasoning to facilitate the dynamic addition of new network types to the heterogeneous network. The novelty is in using semantic reasoning with cross-layer parameters from heterogeneous network architectures to manage and optimize the performance of the networks. The concept is demonstrated through the use of three network architectures: 1) wireless mesh network; 2) long-term evolution (LTE) cellular network; and 3) vehicular ad hoc network (VANET). These networks utilize nonoverlapped frequency bands and can operate simultaneously with no interference. The proposed heterogeneous network was evaluated using ns-3 network simulation software. The simulation results were compared with those produced by other networks that utilize multiple transmission devices. The results showed that the heterogeneous network outperformed the benchmark networks in both urban and VANET scenarios by up to 70% of the network throughput, even when the LTE network utilized a high bandwidth.

**Index Terms**—Heterogeneous networks, LTE, ontologies, reasoning, semantic technologies, WMN.

## I. INTRODUCTION

THE INTERNETWORKING of different wireless technologies, particularly the long-term evolution (LTE) networks and the IEEE 802.11-based wireless mesh networks (WMN), is one of the key opportunities in developing the next generation of wireless networks. The use of

unlicensed frequency bands such as Wi-Fi with the LTE network increases the network capacity and reduces the cost of obtaining more LTE-licensed frequencies. LTE networks are used to avoid low-quality Wi-Fi links and connect island nodes if a link failure occurs. The use of vehicular ad hoc networks (VANET) provides an opportunity to extend LTE and WMN, increase network capacity, and deliver more services to clients. The design of heterogeneous systems is highly complex due to their dynamic nature and the diversity of the associated devices and resources. One possible way to simplify the complexity is to use cognitive networks. A cognitive network is a paradigm that utilizes network characteristics as input and employs reasoning mechanisms to enhance the network performance and simplify the complexity of managing modern wireless networks [1]. The main goal is finding the actions that move the network from a current situation to a desired situation; this tends to be a non-deterministic polynomial time (NP) hard problem [2]. The challenge that the cognitive network model faces in heterogeneous WMNs is securing the quality of service (QoS) characteristics of multiple network architectures and finding the optimal solution using reasoning.

The above challenge is addressed in this paper through the use of Semantic Web technologies and fuzzy reasoning. In particular, Semantic Web technologies provide a mechanism for formal representation of types, properties, and relationships among data in a given domain. Fuzzy reasoning, on the other hand, enables new relationships to be inferred based on data and rules.

The paper advocates the use of semantic reasoning based on ontologies and cognitive networks to abstract the network infrastructure from the control system and improve the performance of the heterogeneous networks. The paper introduces a semantic cognitive network framework, FuzzOnto, to improve the use of multiple radio access networks and separate the control from data transmission. This improves the heterogeneous system performance and creates an extendable middleware that allows more network types to be added in a dynamic, seamless fashion through the use of ontologies and semantic rules. The proposed cognitive network framework contains an extendable middleware comprising a semantic knowledge base and a semantic inference engine. The semantic knowledge base uses ontologies and a semantic rule base to express the relationships between cross-layer parameters from each network device and simplify the process of capturing these parameters. The semantic inference engine uses fuzzy reasoning to control different network architectures; it selects

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the transmission device by employing ontology instances in the knowledge base and the rule base. The reasoning system provides the mechanism to configure automatically different communication systems and to forward traffic demands through suitable transmission devices without the need to customize the software of the transmission devices or update the other layers of the Internet protocol stack. The use of a semantic inference engine enables each node in the heterogeneous network to be self-configured and aware of the surrounding environment and any additionally installed transmission devices. This work adapts the Ontology Web Language (OWL) and Resource Description Framework (RDF) for use in heterogeneous wireless mesh networks.

The paper is organized in six sections. Section II highlights the related work on wireless networks, cognitive and intelligent networks, and semantic technologies for wireless networks. Section III introduces the cognitive network framework proposed in this work. Section IV describes the proposed semantic system, which is then experimentally evaluated in Section V. Finally, Section VI offers concluding remarks and suggestions for future work.

## II. RELATED WORK

The scenarios studied in this research include three types of communication networks that use the non-overlapping frequency bands of each transmission technology: WMN, LTE and VANET. After briefly introducing these network architectures, this section highlights related work on cognitive networks and semantic reasoning in wireless networks.

### A. Wireless Networks

The first network architecture utilized in this study is the WMN. WMNs employ Wi-Fi to establish a network without a centralized infrastructure in which some wireless nodes have a wired connection to the Internet Gateway [3]. Other mesh nodes are used as relay nodes to propagate data to and from the Gateway. WMNs are an economical method of implementing a backbone network for a large area through a multi-hop wireless network. Wi-Fi is an economical choice for network operators as the cost of Wi-Fi chipsets continues to decrease and Wi-Fi hotspots are being installed in hotels, airports, and other public places. However, WMNs suffer from some drawbacks due to the multi-hop nature of the network, such as the interference among the communicating and isolated island nodes, which are result of node failure.

The second type of network architecture used in this work is the LTE network [4]. LTE networks utilize licensed frequency bands, which add extra costs and might not be available in all regions. LTE networks consist of two main parts: the LTE base station, or evolved Node B (eNodeB or eNB) base station, which provides cell coverage, and the evolved packet core (EPC), which connects the network to the Internet.

The IEEE 802.11p standard is part of the wireless access in vehicular environments (WAVE) [5] that supports wireless access in VANETs. VANETs exchange and broadcast safety-related and service application data between moving vehicles, or vehicle-to-vehicle (V2V), and between vehicles

and roadside units, known as vehicle-to-infrastructure (V2I) communication. IEEE 802.11p operates in a dedicated short-range communication (DSRC) band of 5.85–5.92 GHz. In this band, one control channel (CCH) is used to transmit safety and control information, while up to six other service channels (SCH) are employed to exchange service information [6].

Radio access technologies for the 5<sup>th</sup> generation networks are expected to serve more traffic demands by 1000–10000-fold [7]. One approach to meet this increased capacity demand is to introduce new spectral resources, for example, the use of high frequency bands, 3–300 GHz [8]. The interoperability between 5G radio technology and other traditional RAN such as LTE and Wi-Fi is essential for improving the frequency efficiency of the 5G networks [9].

### B. Cognitive and Intelligent Networks

The cognitive network is a network paradigm that was recently developed to reduce network complexity and enhance network performance. Cognitive networks are characterized by their extensibility, flexibility, and proactivity as well as their ability to use network metrics as input and produce an action to the network as output. They could provide improved network performance compared with traditional networks [1].

Several studies use learning and artificial intelligence (AI) techniques to improve the cognitive network process [10]–[15]. For example, a cognitive network for disaster situations [10] employs a transmission device as a control device to exchange the network QoS parameters, and then an algorithm based on the analytic hierarchy process (AHP) selects the most suitable link for handling traffic transmission. Other studies have used reinforcement algorithms to create a cognitive process, which mitigates the impact of interference in wireless networks [12]–[15]. For example, reinforcement learning is employed in macrocells to collaborate and learn from other cells in order to reduce the power required by a macrocell base station and enhance the coordination of inter-cell interference [12], [13]. Another study used reinforcement algorithms to create cooperation between different networks and avoid interference due to the activation or deactivation of some services [15].

Other studies use fuzzy logic with cross layer parameters to create a cognitive network that works independently from the underlying technology [16], [17]. Fuzzy mapping is employed to create a shared knowledge base that each node could use to select the transmission technology in order to access the network. The QoS parameters are obtained from the network layers, represented using fuzzy numbers and stored in the shared knowledge base. When a node needs to connect to a network, it uses the shared knowledge base to measure the quality of each network and select the best. The use of a shared knowledge base is useful for a small network with central access, but for a metropolitan area network it could cause overhead spatially with WMNs, as users have multiple nodes to choose from in addition to the LTE and VANET networks.

The advantage of cognitive systems is that they allow relationships to be established between various wireless networks.

In this paper, the current state-of-the-art is advanced through the introduction of a novel reasoning system capable of inferring optimal actions and configuring the heterogeneous network automatically using ontologies. Furthermore, the use of semantic technologies and reasoning allows the management of the heterogeneous network to be separated from the data transmission.

### C. Semantic Technologies for Wireless Networks

Ontologies are used to create relationships between technology-dependent features. Inference engines, or reasoners, utilize ontology instances to infer the appropriate action to be taken based on a set of predefined rules. The data in the ontology are defined as a set of relationships between resources, while the reasoner infers new relationships based on data and rules. Relevant reasoning systems have been developed to validate the ontology design, check the consistency of the relationships between ontology classes, and regenerate new relationships [18]. This type of reasoning has been embedded as a plug-in in ontology design tools, such as Protégé [19] and OilEd [20]. A number of studies in wireless sensor networks (WSNs) [21]–[26] use data from sensor nodes to build the ontology knowledge base. In particular, ontologies and semantic reasoning are employed in routing algorithms for WSNs [21], [22] to select the next hop and forward data based on the data observed by the sensors. For instance, if a heating sensor observes a high temperature, the node adds semantic information, such as the location of the high-temperature area, to the feedback message. The reasoner in the neighboring nodes uses the location information to avoid forwarding the data through the high-temperature area since there is a possibility of fire [21]. Another routing algorithm utilizes ontologies to describe node information, including node position, residual energy, communication distance, and detection distance, to understand the status of the neighboring nodes. If more than one node is available to perform the same task, then the node closest to the sink with the higher residual energy is selected [22].

Ontologies and semantic reasoning have also been used to automatically find and access WSNs services [23]–[26]. Examples include monitoring the service type of each node by collecting the data and service type in a cluster head node [23] or generating an abstraction model for the resource specification in the WSNs [24]. Accessing the services in WSNs requires semantic annotation of the available services as well as binding these services with such network properties as service properties (temperature), location properties (the sensor node location), and physical properties (processor type and memory size), which aids the search and retrieval of the services requested by the end user [25], [26].

Ontologies and semantic reasoning systems have also been used to assist with the management, specifically the topology discovery, of heterogeneous, multi-tier networks [27], [28]. If an ontology is developed for WSN, ad hoc, and wired networks, then another ontology can map the concepts from each ontology into a single common ontology. For example, network nodes can utilize different address types, such

as an Internet protocol (IP) or node ID, and the address in each ontology can be mapped to a property in the common ontology. The properties of the network devices are retrieved by standard network management systems to create the instances in the knowledge base. Ontology Web language (OWL)-S has been also used to develop network management systems [29]–[32]. OWL-S specifies the data type using ontology classes to assign semantic meanings to the data retrieved from the network management system. The network manager can then use the ontology classes to indicate the network status using standard reasoning and querying systems.

Ontology and semantic reasoning has been also used in cognitive radio communication to create wireless nodes that are capable of understanding the content of the information to be transferred as well as the abilities of the node itself, the destination, and the environment [33]–[35]. For example, a node may utilize ontology instances to express its ability to satisfy the transmission needs, which helps to deduce the optimal operating parameters.

Although ontologies and semantic reasoning have been used in wireless communication systems, research on the management and optimization of heterogeneous networks using cross-layer parameters from different network architectures is still limited. Current communication systems utilize ontologies to represent information from the application layer to define a set of relationships and classes that could be used to improve network performance. Different from the current approaches, the semantic reasoning system proposed in this paper uses ontologies to represent the QoS parameters from various network architectures and from multiple layers of the network protocol stack to automatically optimize and configure the heterogeneous network architecture. This semantic reasoning system regulates and controls the heterogeneous networks and provides the flexibility to extend the communication system through a set of rules rather than customizing the software on each network device.

This paper contributes to the body of knowledge in this area by proposing a cognitive network framework that can manage and optimize the use of heterogeneous networks. The semantic system developed allows more network architectures to be added through the use of ontologies and rules. Furthermore, an inference engine is proposed to optimize the heterogeneous networks through the use of fuzzy reasoning, the relationships in the heterogeneous networks ontology, and a rule base.

## III. PROPOSED COGNITIVE NETWORK FRAMEWORK

From a research perspective, the proposed cognitive network framework can be defined as a semantic-based system that collects QoS parameters from different layers in the network protocol stack and establishes an interface between different wireless network architectures. In other words, this framework facilitates the process of using, managing, and combining different wireless network architectures by separating the heterogeneous network infrastructure from the control system. Fig. 1 shows the block diagram of the proposed cognitive

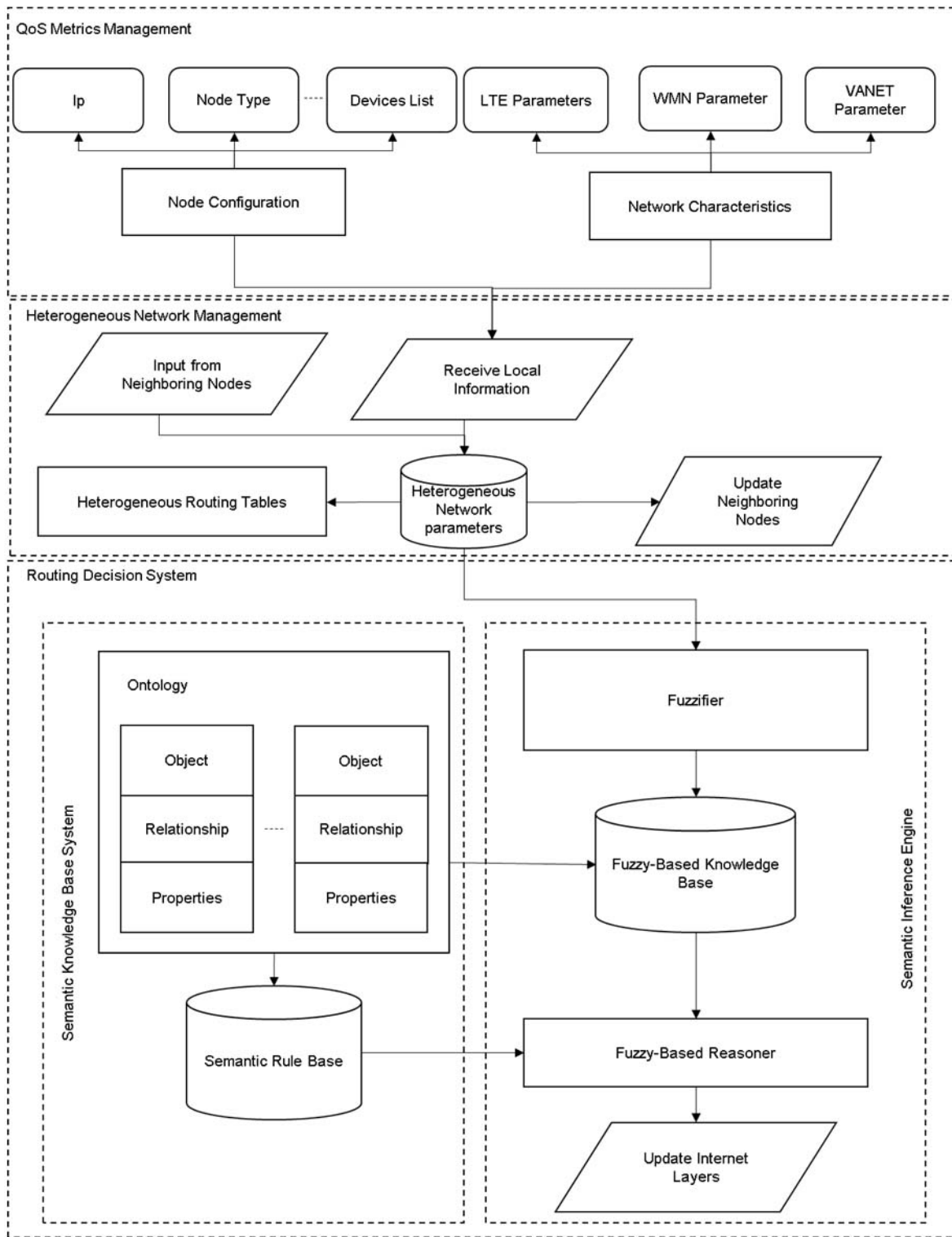


Fig. 1. Proposed cognitive network framework.

framework, which has three main parts: a QoS metrics management system, heterogeneous network management system, and routing decision system. The QoS metrics management system obtains node configuration parameters and various network characteristics, such as the load, quality of the communication channel, and transmission rate of the Wi-Fi device. The heterogeneous network management system manages

the process of exchanging information between neighboring nodes using different network architectures; this process was described in [36]. The routing decision system uses, manages, and adds different wireless network architectures. It consists of a semantic knowledge base, which uses the ontology and rule base to optimize and control the heterogeneous wireless network, and a semantic inference engine, which uses



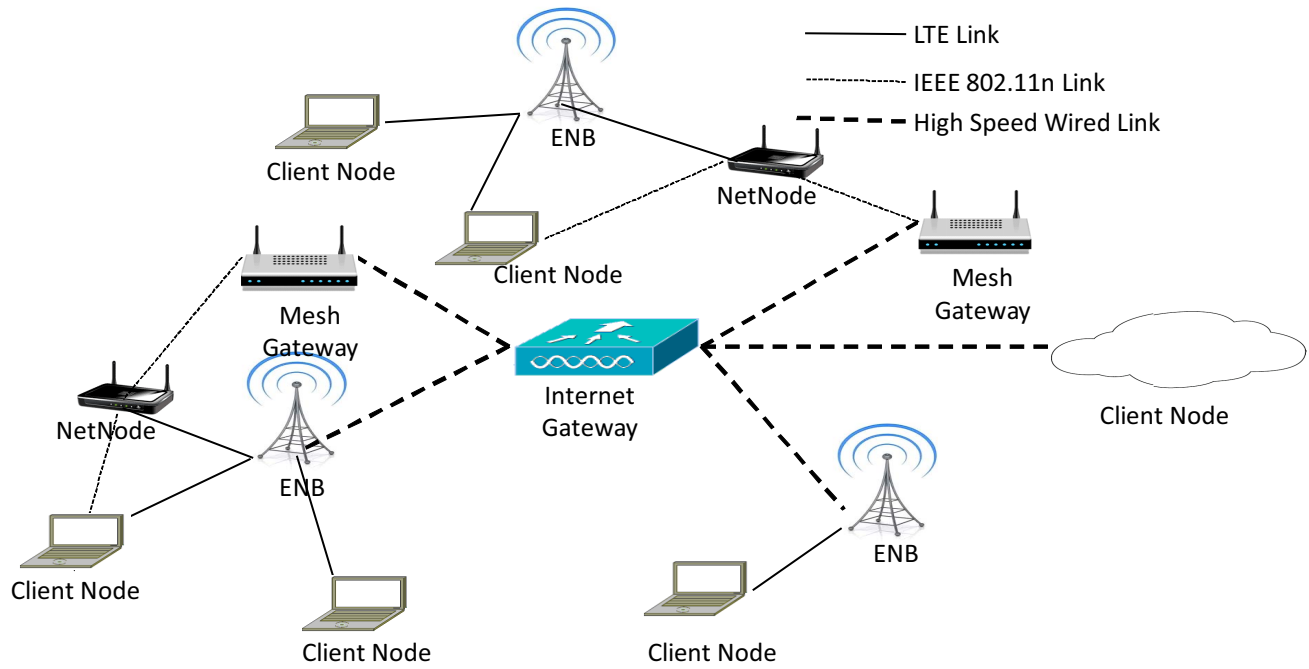


Fig. 2. The urban heterogeneous network scenario.

a fuzzy-based reasoner to infer a set of actions to optimize the heterogeneous network. During the operation of the cognitive network framework, the QoS metrics management system collects local parameters from the network protocol stack and passes these data to the heterogeneous network management system. The heterogeneous network management system stores the local parameters with the data obtained from the neighboring nodes in a database. A fuzzifier system then processes the data from this database to obtain the fuzzy set of heterogeneous network parameters, which are stored as instances of the ontology is used in this phase. The reasoner then sends the decision to the classes and properties in the fuzzy-based knowledge base. A fuzzy-based reasoner then uses the instances of the ontology in the knowledge base and the set of rules in the rule base to infer the next actions in the heterogeneous wireless network and to select the network architecture that can handle the transmission; this fuzzy-based reasoner is based on the Mamdani reasoner [37]. A centroid method, or center of gravity, of defuzzification is used in this phase. The reasoner that sends the decision to the layer in the Internet protocol stack that is responsible for performing the required action. As previously mentioned, the heterogeneous network model utilizes three different architectures, WMN, VANET, and LTE, to use the different frequency bands of each network and enhance their overall capacity. WMNs and VANETs utilize IEEE 802.11n and IEEE 802.11p, respectively. Two scenarios are proposed in this study to evaluate the semantic reasoning system for heterogeneous wireless networks. The first scenario is the urban heterogeneous network scenario, in which different amounts of traffic demands are applied to the system. The second scenario is the VANET heterogeneous network scenario, which uses several network architectures to demonstrate how the proposed semantic reasoning system could be extended to control other

network types. In the first scenario (Fig. 2), the client nodes consider the coexistence of WMN and LTE networks and transmit data to the Internet using one of the available radio access networks (RAN) (IEEE 802.11n or LTE) in the heterogeneous network while the second scenario (Fig. 3) introduces the use of the VANET network.

The heterogeneous network uses the following node types:

- **NetNodes:** These heterogeneous nodes of the WMN form the network infrastructure and are equipped with both Wi-Fi (IEEE 802.11n) and LTE capabilities.
- **ClientNodes:** These heterogeneous nodes of the WMN represent the end users and have Wi-Fi (IEEE 802.11n) and LTE capabilities.
- **Mesh Gateway:** These nodes have Wi-Fi (IEEE 802.11n) and wired connections that connect the WMN to the Internet through the Internet Gateway.
- **LTE base stations:** These stations are also known as eNodeB or eNB base stations.
- **Internet Gateway nodes:** These nodes connect different networks to the Internet using a high-speed wired network.
- **802.11pCars:** These cars are part of the VANET network and use only IEEE 802.11p devices.
- **HetCars:** These cars are part of the VANET network and are equipped with both IEEE 802.11p and LTE RANs.
- **HetRSide:** These roadside units use IEEE 802.11p, 802.11n, and LTE RANs. These nodes connect the cars on the road to the WMN and LTE networks.

In this heterogeneous network, the ClientNodes connect to the Internet through IEEE 802.11n or the LTE network. The HetCars connect to the Internet either through IEEE 802.11p or the LTE RAN. 802.11pCars connect to the Internet through IEEE 802.11p. The NetNodes are responsible for forwarding client data to and from the Internet using either LTE or

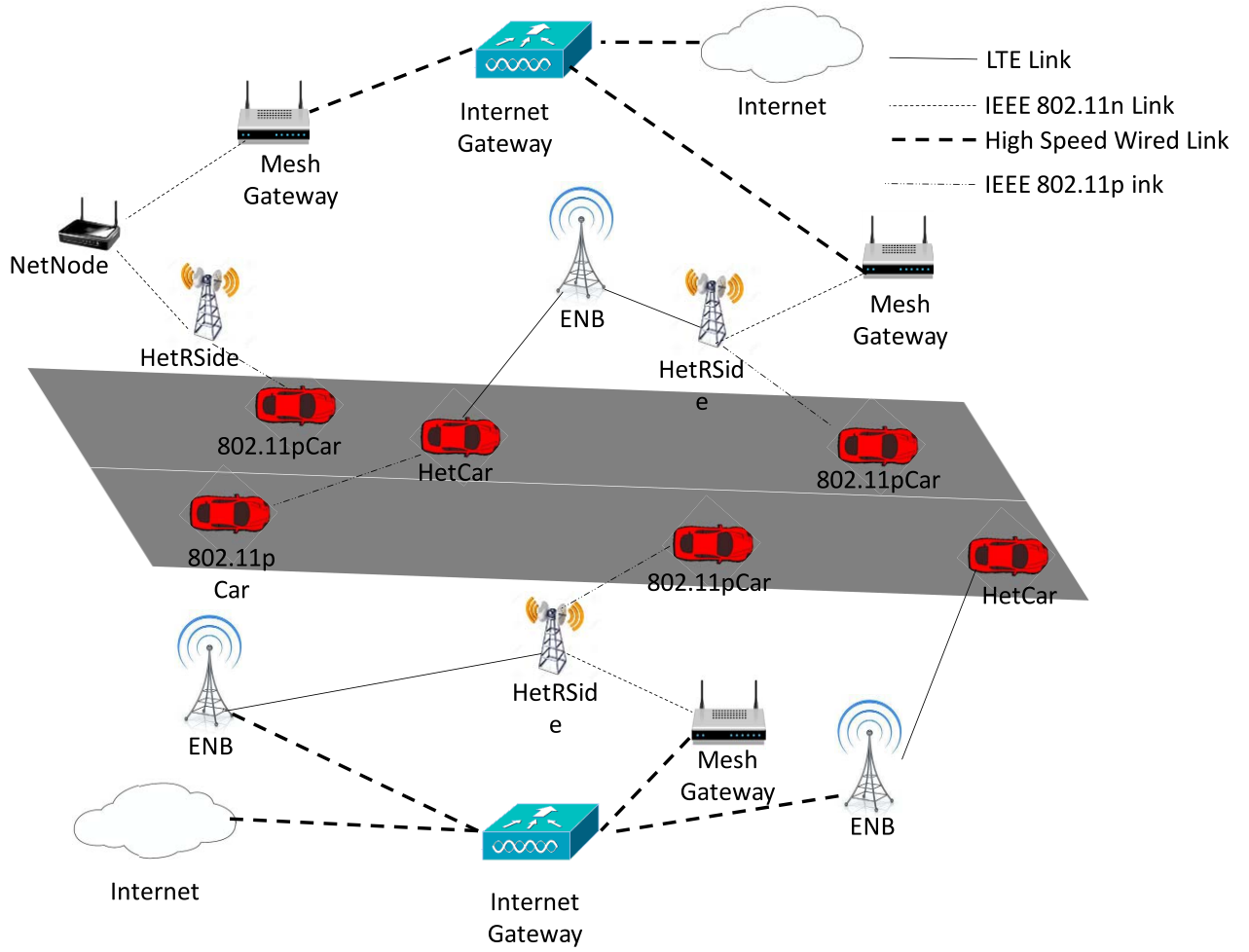


Fig. 3. The VANET heterogeneous network scenario.

IEEE 802.11n based on QoS parameters. The HetRSides communicate with 802.11pCars and HetCars through the IEEE 802.11p and then forward the data using either LTE or IEEE 802.11n to the Internet. The proposed reasoning system allows ClientNodes to forward the data from other clients to the Internet. Enabling ClientNodes to participate in the network infrastructure reduces the load on the network backbone and also allows users to gain credits for forwarding data. The selection of a particular transmission technology to forward the data is based on QoS parameters described in the next section.

#### IV. SEMANTIC SYSTEM

The semantic system consists of a semantic knowledge base and a semantic inference engine. The semantic knowledge base is based on the recently proposed ontology of heterogeneous networks [38] and a rule base. The novel semantic inference engine utilizes fuzzy logic to create instances of the ontology in the knowledge base that represent the QoS parameters of each RAN. The use of fuzzy logic is appropriate because of the uncertainty of the network QoS parameters, which may result in inaccurate information. Fuzzy membership functions are used to produce a fuzzy set of network parameters. Finally,

a fuzzy-based reasoner utilizes the rule base to autonomously control the various transmission technologies.

##### A. Heterogeneous Network Ontology

The QoS parameters of each network in the heterogeneous network are stored using ontology classes, properties, and relationships. Standard ontology languages such as OWL [39] and resource description framework (RDF) or RDF schema [40] define classes, subclasses, properties, and relationships. Instead, this study uses extensible markup language (XML) as a platform to create ontology classes of heterogeneous wireless networks. XML is platform independent, which enables the proposed semantic reasoning system to be used with any smartphone, personal computer, or computer-based object. Moreover, the ontology suggested in this work is relatively simple and does not need all the expressiveness that is provided by other standard ontology languages. The XML-based approach leads to a simple, lightweight knowledge base system that could work on wireless nodes with limited processing resources. The ontology generated a set of classes and properties to represent the heterogeneous network characteristics, as shown in Tables I and II, respectively. Fig. 4 shows the ontology graph of the proposed heterogeneous wireless

TABLE I  
ONTOLOGY CLASSES

| Class Name      | Parent Class | Description                                       |
|-----------------|--------------|---|
| HetNet          | -            | heterogeneous wireless network                    |
| Node            | HetNet       | wireless and wired nodes                          |
| LTENode         | Node         | nodes equipped with LTE device                    |
| NetNode         | Node         | nodes equipped with LTE and IEEE 802.11n          |
| VanetNode       | Node         | nodes equipped with IEEE 802.11p                  |
| HetCars         | VanetNode    | wireless nodes equipped with LTE and IEEE 802.11p |
| IEEE802.11pCars | VanetNode    | wireless nodes equipped with IEEE 802.11p         |
| RAN             | HetNet       | RAN type  |
| LTENet          | RAN          | LTE RAN   |
| Wi-FiNet        | RAN          | Wi-Fi RAN   |
| IEEE802.11nNet  | Wi-FiNet     | wireless devices of type IEEE 802.11n             |
| IEEE802.11pNet  | Wi-FiNet     | wireless devices of type IEEE 802.11p             |

network, in which the classes, subclasses, and properties are shown.

### B. Fuzzy-Based Knowledge Base

The network characteristics and node configuration parameters are stored in the fuzzy-based knowledge base as instances of the heterogeneous network ontology. The QoS parameters of each RAN are transformed from crisp points ( $x$ ) to fuzzy sets  $[x, \mu(x)]$  in  $U$ , where  $\mu$  is the membership function  $U \in [0 - 1]$ . In this model, the QoS parameters are fuzzified using predefined membership functions, as shown in Fig. 5–8. The membership functions are selected empirically to reflect changes in the QoS parameters. For example, in Fig. 5 the membership of the LTE load returns zero when the load is below 10%. Then, the load starts increasing gradually until it reaches 70%. Finally, the load on the system is considered high. These values are selected by testing the system performance using various loads and different simulation scenarios. Another example is shown in Fig. 8, in which each value in the Wi-Fi success rate could affect the performance of the heterogeneous network. Thus, the membership function returns a different fuzzy degree for each transmission rate. The membership functions were tested empirically using ns3 simulation. The fuzzification process maps the input value to names and degrees of membership functions. The set of notations used in this paper is listed in Table III. The fuzzification step is performed on the QoS parameters for each transmission technology. The LTE network employs two parameters to estimate the quality of the network. The first parameter is the load on

TABLE II  
ONTOLOGY PROPERTIES

| Property             | Description   |
|----------------------|---|
| hasLTELoad           | load on the LTE network   |
| hasLTEChannelQuality | channel quality of the LTE network  |
| hasWi-FiSucRate      | Wi-Fi network success rate of transmitting data packets   |
| hasWi-FiChannelRate  | Wi-Fi network transmission rate   |
| hasLTESW             | strength weight to select LTE; this property is inferred from the rule base   |
| hasWi-FiWeight       | strength weight to select Wi-Fi network   |
| hasRAND              | decision to select the rand   |
| hasNeigh             | one-hop neighbors of wireless node; this value is obtained from the routing table   |
| hasShortestPath      | next hop node with the shortest path to the mesh gateway; this value is obtained from the routing table                             |
| SelectNextHop        | decision of selecting the node as a next hop  |
| hasHops              | defines the number of hops from the node to the mesh gateway along the shortest path; this value is obtained from the routing table |
| hasLCD               | defines the link connectivity duration (LCD) between two neighboring nodes in VANET   |

the network, which is calculated using (1) based on the number of resource blocks (RBs) assigned to each node.

$$LTE L_t^d = \frac{RB_t^d}{RBMax} * 100\%, \quad (1)$$

where  $LTE L_t^d$  is the load on the LTE network for node  $d$  at time  $t$ ,  $RB_t^d$  represents the number of allocated resource blocks for node  $d$  at time  $t$ , and  $RBMax$  is the number of available resource blocks for the LTE cell.  $LTE L_t^d$  is mapped to a fuzzy set using the membership function of the LTE load (FLL) in Fig. 5.

The second parameter for the LTE network is the channel quality indicator (CQI), which is collected by the eNB base station. CQI provides information on the quality of the communication channel, while the eNB selects the appropriate modulation and coding method based on the CQI feedback from the user equipment (UE). In this work, the channel quality value is mapped to the corresponding fuzzy degree in the membership function, as shown in Fig. 6. The CQI for the best channel quality is 1 while 0 means it is out of range.

In this paper, the WMN uses a recently proposed rate adaptation algorithm based on reinforcement learning (*RARE*) [41]. It has been developed for multi-hop WMNs where the nodes that are competing to access the shared channel are considered in the calculation of the transmission rate. *RARE* employs both the load and the interference to calculate the transmission rate. The node with the higher transmission rate has a better link

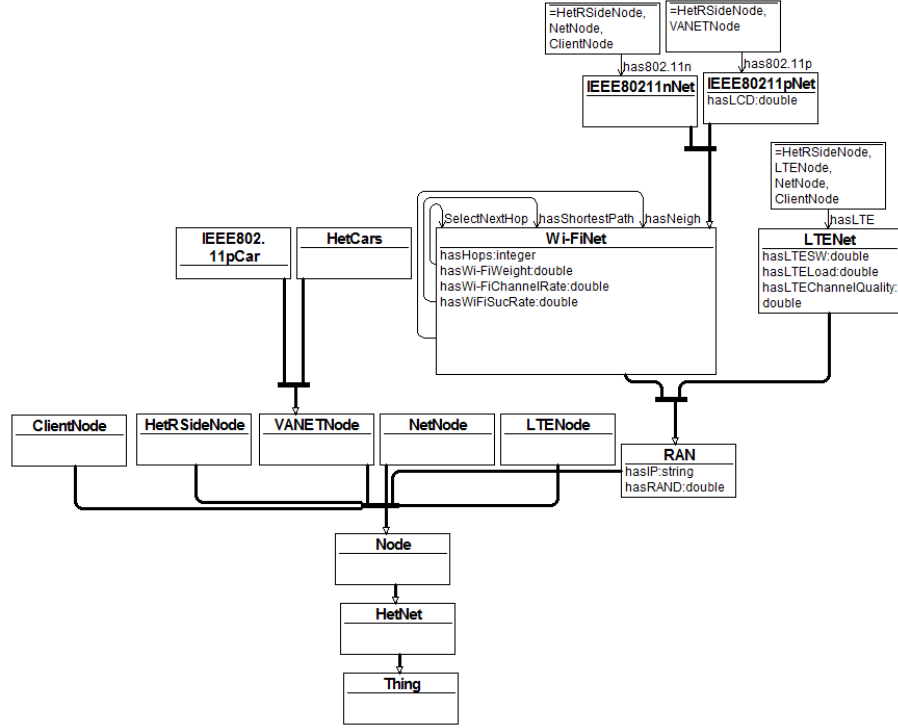


Fig. 4. Ontology graph of the heterogeneous WMN.

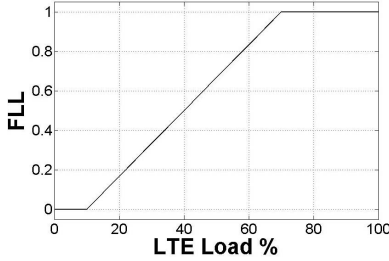


Fig. 5. LTE load membership function.

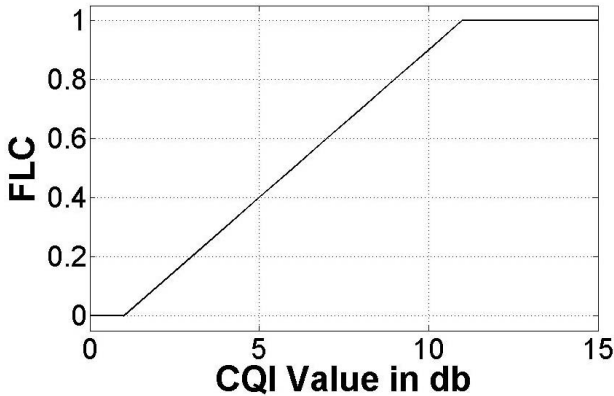


Fig. 6. CQI membership function.

quality. It sets the transmission rate to optimize the network performance and mitigate the impact of interference.

The WMN also uses two parameters to estimate the channel quality, the transmission rate of each node during time slot  $t_i$ ,

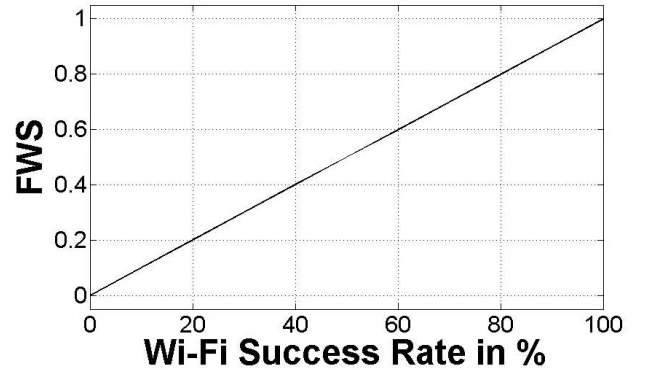


Fig. 7. Wi-Fi transmission rate membership function.

and the probability of accessing the channel. The membership function in Fig. 7 defines eight fuzzy degrees for the transmission rates in IEEE 802.11n (15, 30, 45, 60, 90, 120, 135, and 150 Mbps) and eight fuzzy degrees in IEEE 802.11p (6, 9, 12, 18, 24, 36, 48, and 54 Mbps). The second parameter is the success rate of the Wi-Fi device in accessing the wireless channel on the node, which is estimated using (2).

$$SRW^d(t_{i-1} - t_i) = \frac{STW^d(t_{i-1} - t_i)}{TTW^d(t_{i-1} - t_i)} * 100\%, \quad (2)$$

where  $SRW^d(t_{i-1} - t_i)$  is the success rate for the Wi-Fi device on node  $d$  since the last update of the transmission rate  $(t_{i-1} - t_i)$ .  $STW^d(t_{i-1} - t_i)$  is the number of successful transmissions for node  $d$  from the interval of the last rate update.  $STW$  is calculated by counting the number of received acknowledgments on the Wi-Fi medium access layer (MAC).  $TTW^d(t_{i-1} - t_i)$  is the total number of transmissions for the



TABLE III  
VARIABLES AND NOTATIONS

| Variable             | Variable Description   |
|----------------------|--|
| $D$                  | a heterogeneous network node   |
| $\Phi$               | a set of all available nodes in the network, $d \in \Phi$  |
| $t_i$                | current time instance  |
| $t_{i-1}$            | previous time instance of $t_i$  |
| $LTEL^d_t$           | LTE device load for node $d \in \Phi$ at time $t$  |
| $RB^d_t$             | number of allocated resource blocks for node $d \in \Phi$ at time $t$  |
| $RBMax$              | number of available resource blocks of the LTE cell  |
| $CQI$                | channel quality indicator for LTE link   |
| $UE$                 | user equipment   |
| $SRW^d(t_{i-1}-t_i)$ | success rate of node $d \in \Phi$ of accessing the Wi-Fi network since the last update of the probability to access the Wi-Fi channel                |
| $STW^d(t_{i-1}-t_i)$ | number of successful transmissions on the Wi-Fi device for node $d \in \Phi$ since the last update of the probability of accessing the Wi-Fi channel |
| $TTW^d(t_{i-1}-t_i)$ | total number of transmissions using the Wi-Fi for node $d \in \Phi$ since the last update of the probability of accessing the Wi-Fi channel          |
| $LCD_{ij}$           | lifetime of communication link between nodes $i$ and $j$   |
| $LCD_{th}$           | LCD threshold value (30 s is used in this work)  |
| $FLL$                | fuzzy set of the LTE load  |
| $FLC$                | fuzzy set of the LTE channel quality   |
| $LSW$                | LTE weight   |
| $FWS$                | fuzzy set of the Wi-Fi success rate  |
| $FWC$                | fuzzy set of the Wi-Fi channel transmission rate   |
| $WSW$                | Wi-Fi weight   |
| $RAND$               | RAN decision   |

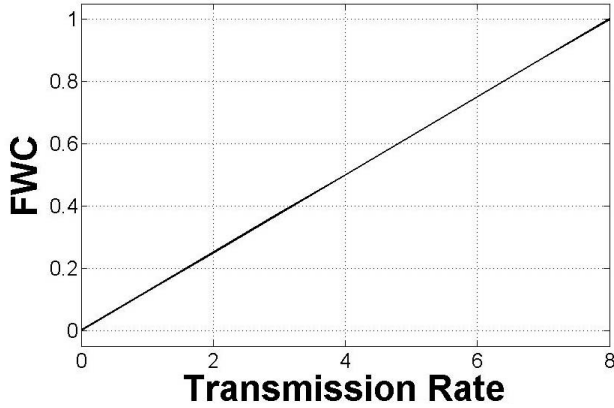


Fig. 8. The success rate for Wi-Fi device (FWS) membership function.

Wi-Fi device on node  $d$  since the previous transmission rate update. For the heterogeneous networks using VANET, the link connectivity duration (LCD) [42] is utilized in selecting the next hop.

The reason for using LCD is the consideration for the movement and velocity of cars since the LCD metric reflects the lifetime of a communication link between two nodes. Equation (3) [42] is used to calculate the LCD.

$$LCD_{ij} = \frac{\sqrt{(\alpha^2 + \gamma^2)R^2 - (\alpha\delta - \beta\gamma)^2} - (\alpha\beta + \gamma\delta)}{\alpha^2 + \gamma^2}, \quad (3)$$

where  $\alpha = v_i \cos \theta_i - v_j \cos \theta_j$ ,  $\gamma = v_i \sin \theta_i - v_j \sin \theta_j$ , and  $v_i$  and  $v_j$  are the velocities of moving cars for nodes  $i$  and  $j$ , respectively.

$\theta_i$  and  $\theta_j$  are the inclination with  $x$ -axes ( $0 < \theta_i, \theta_j < 2\pi$ ).  $\beta = x_i - x_j$  and  $\delta = y_i - y_j$ , where  $x_i, y_i$  and  $x_j, y_j$  are the Cartesian coordinates of nodes  $i$  and  $j$ .  $R$  is the transmission range of the IEEE 802.11p. The LCD parameter is calculated for adjacent nodes to estimate the lifetime of the wireless link.

Fig. 9 shows an example of an ontology instance for a NetNode using fuzzy logic to weight each RAN parameter. The instances of the ontology are stored in the knowledge base using the fuzzy member functions defined in Figs. 5–8. For example, the value of the hasLTELoad property is 0.55, which is the fuzzy set of the LTE load (LL) calculated using Fig. 5, where 0.55 corresponds to 45% of the available resources being allocated to the node. A similar method is applied to compute hasLTEChannelQuality, hasWiFiChannelRate, and hasWi-FiSuccessRate using the membership functions in Figs. 5, 6, and 8, respectively.

### C. Semantic Rule Base and Fuzzy-Based Reasoning System

This section defines a set of rules that are created based on the classes, subclasses, and relationships in the ontology. The fuzzy-based reasoning system uses these rules, in addition to the instances of the ontology in the knowledge base, to control the different network architectures and obtain the best RAN on the node for packet transmission. The reasoning system is developed to control the three networks (WMN, VANET, and LTE), and each network type uses a different RAN (IEEE 802.11n, IEEE 802.11p, and LTE).

The fuzzy-based reasoning system uses a set of rules to obtain the RAN with the best link quality. The rule base is

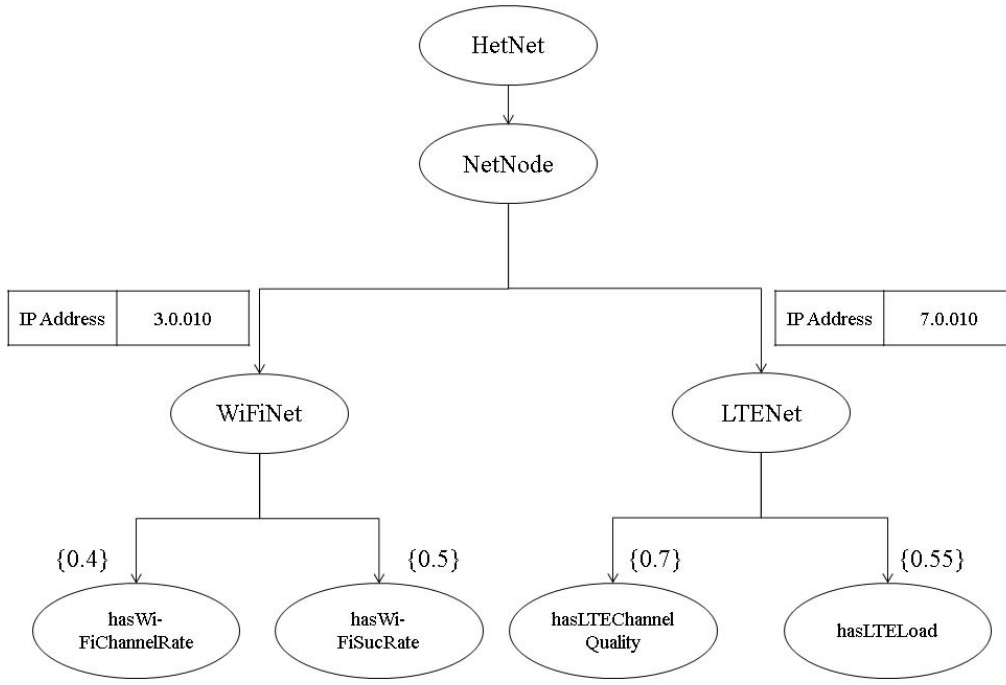


Fig. 9. Graph of the knowledge base instance for a NetNode.

responsible for checking whether the ClientNodes accept other nodes packets to relay. The users of the ClientNodes can set them to participate in the network infrastructure or not. By participating in the network infrastructure, the ClientNodes can reduce the load on the heterogeneous network and the user could obtain some benefits (e.g., getting a discount).

The fuzzified values obtained from the QoS parameters of each RAN are employed to evaluate the set of rules using the fuzzy-based reasoning system. The proposed fuzzy-based reasoner utilizes the rule base and the instances of the ontology in the knowledge base to infer the best RAN. The rules were formed in the Semantic Web Rule Language (SWRL) [43]. The Pellet reasoner [44] was used to check the consistency of the ontology. Fig. 10 shows the flowchart of the FuzzOnto reasoning. The process of selecting the transmission technology starts if the node type is of class HetNet. *LSW* is the weight of the LTE device and is the result of a fuzzy “and” operation of a fuzzy set of the LTE load (*FLL*) and fuzzy set of the LTE channel quality (*FLC*) obtained from Figs. 5 and 6, respectively, as explained earlier. Similarly, the weight of the Wi-Fi device (*WSW*) is calculated using a fuzzy “and” operation of a fuzzy set of the Wi-Fi success rate (*FWS*) and fuzzy set of the Wi-Fi channel transmission rate (*FWC*) computed from Figs. 7 and 8, respectively.

Mamdani fuzzy inference is then used to select the RAN. Mamdani fuzzy inference consists of three main modules: the fuzzifier, the rule base, and the defuzzifier. The fuzzifier obtains the QoS parameters for each RAN and stores the fuzzy set as an instance of the ontology in the knowledge base. The fuzzified values are used to evaluate the rule base to obtain the radio access network decision (*RAND*). The final step is defuzzification, which is the process of mapping the output fuzzy set back into a crisp value. The most commonly used method is the centroid method, which was developed by

Sugeno in 1985. The only problem with this method is that it is difficult to be applied for complex membership functions. However, in this work, the membership functions have a simple trapezoid shape. The centroid defuzzification is calculated using (4)

$$RAND = \frac{\int \mu_i(x)xdx}{\int \mu_i(x) dx}, \quad (4)$$

where *RAND* is the defuzzified value of the output fuzzy set and  $\mu$  is the aggregated membership function for the output value. The value of *RAND* is used to select the transmission technology. The next step is to check which transmission technology is selected; if LTE is selected, the traffic demand is transmitted directly to the eNB base station. If Wi-Fi is selected, the node class is checked. In case the node type is ClientNode or NetNode, the shortest path in terms of hop count is used to select the next hop. If two nodes have the same number of hops to the Mesh Gateway, then the node with the higher WSW is selected to forward the packets. If two nodes have the same WSW, then NetNodes are selected over ClientNodes to reduce the load on the client nodes.

If the node is of type HetCar or 802.11pCar, the algorithm selects the next hop with the shortest path to the Mesh Gateway, which has an LCD greater than  $LCD_{thr}$  (in this study,  $LCD_{thr}$  is equal to 30 s). If more than one node has the same hop count, then the next node is selected based on the node type. HetRSide nodes are selected before HetCars and 802.11pCars, and HetCars nodes are selected before 802.11pCars.

In the VANET heterogeneous network scenario, three types of nodes are included in the heterogeneous network. The first two types are vehicles equipped with both IEEE 802.11p and LTE (HetCars) and vehicles equipped with only IEEE 802.11p (802.11pCars). These moving nodes are sending

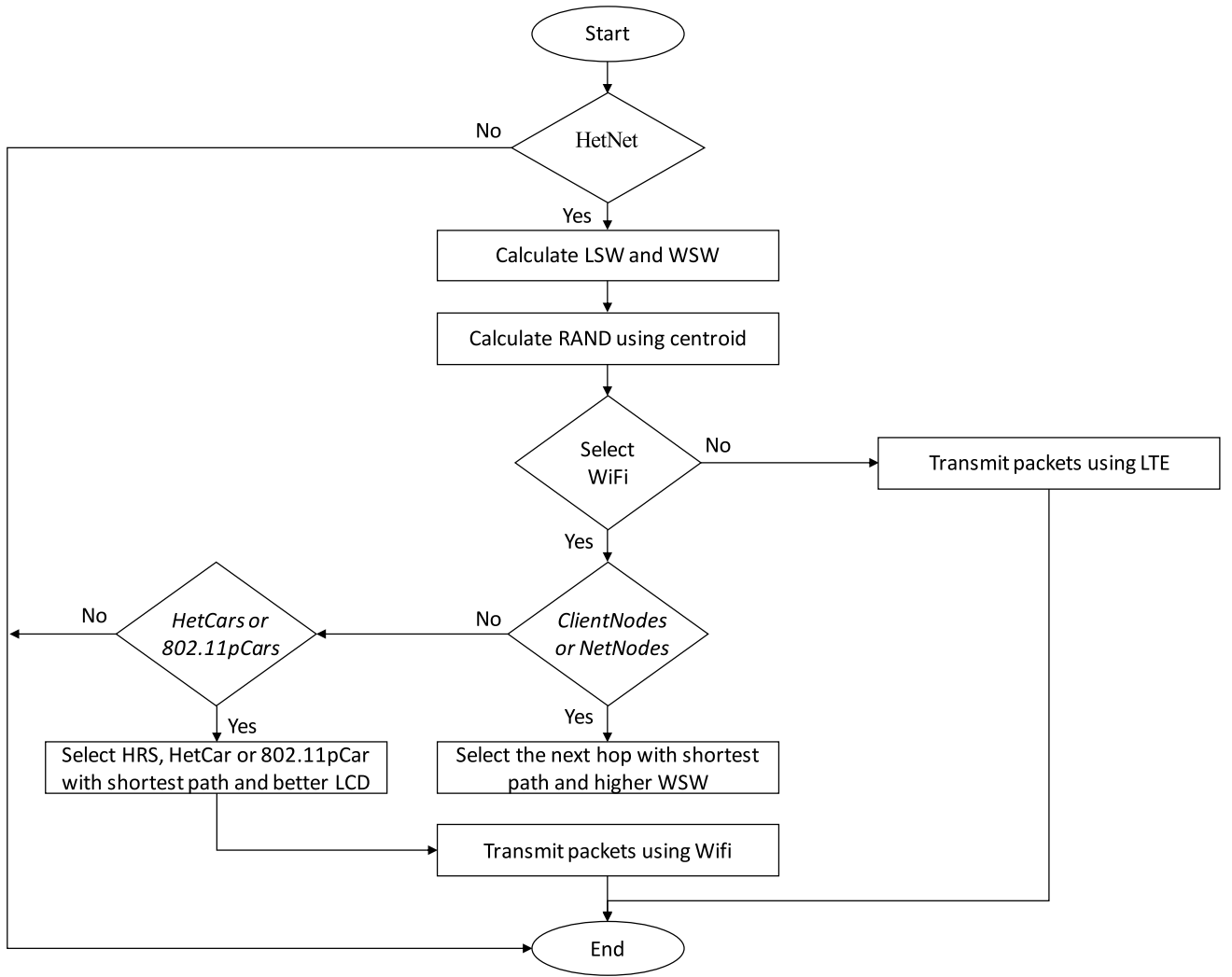


Fig. 10. FuzzOnto reasoning flowchart.

data to the roadside units (HetRSide). This study considers the V2I communication.

## V. PERFORMANCE EVALUATION

The proposed cognitive network framework was evaluated using Network Simulator version 3 (ns-3) [45], which is a widely used simulator for networking systems. The LENA module [46] was employed by the ns-3 simulator to simulate the LTE network. The proposed cognitive network framework, called FuzzOnto, was compared in terms of throughput and packet delivery ratio (PDR) with LTE-only network, Wi-Fi-only network, and a number of networks that use different wireless technologies. These networks are listed below:

- Balance: this network distributes the traffic evenly between the LTE and IEEE 802.11n wireless networks;
- Rand: this network randomly selects the transmission technology;
- VH: this wireless network performs a vertical handover between the LTE and Wi-Fi networks; it consists of ClientNodes and a WMN that uses the Wi-Fi network, and the client can choose between sending through the

LTE or the WMN as two separate networks. The algorithm of selecting the LTE or WMN is based on [42]; and

- Learning: this heterogeneous network, proposed in [36], uses reinforcement learning but does not employ fuzzy logic to represent the QoS parameters of the networks.

In addition, VanetMobiSim 1.1 [47] was used to simulate vehicle mobility in the VANET heterogeneous WMN. Intelligent Driver Model with Lane Changes (IDM\_LM) is used to simulate realistic scenarios with multiple lanes and the possibility for vehicles to change lanes and overtake each other. The use of this scenario helps to simulate moving cars with variable velocities and random movements. The bandwidth in the LTE network is represented by the total number of RBs available for the user equipment in the network. In this work, 100 and 75 RB were used in FuzzOnto compared with the 100 RB that are used in benchmark networks.

### A. Urban Heterogeneous Network

This scenario involves a random number of ClientNodes distributed in a 1000 m<sup>2</sup> area, three eNB base stations, and 100 NetNodes that formed the backbone of the heterogeneous

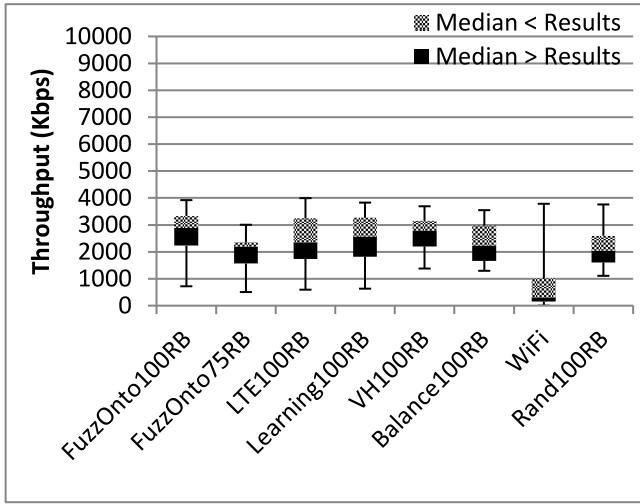


Fig. 11. Average throughput for an urban heterogeneous network with a low load.

network. Three different scenarios were used to evaluate the proposed network. In each scenario, 30 ClientNodes were randomly distributed, while different loads were applied to the network (low, medium, and high). The simulation results for each scenario show that the heterogeneous network that used the proposed cognitive network framework outperformed the benchmark networks in terms of throughput and PDR. Figs. 11–16 show the network performance for the FuzzOnto network compared with the benchmark networks. Box and whisker graphs are employed to visualize the results. Each chart has four quartiles; the lower box shows the results that are less than the median while the upper box represents the results that are greater than the median. The upper and lower whiskers represent the highest and lowest values of the results.

The results indicate that FuzzOnto performed better when the load on the network was high. In Fig. 11, the traffic demands were not high, and FuzzOnto did not show a significant improvement in throughput compared with the LTE, Wi-Fi, Learning, Balance, and Rand networks. In Figs. 12 and 13, the load was higher, and the results indicate that FuzzOnto performed better than the benchmark networks. For instance, in Fig. 12, FuzzOnto achieved average throughput with up to 46% higher than the other networks when the median of the results was compared. The PDR for the urban heterogeneous network is shown in Figs. 14 to 16; the results indicate that FuzzOnto outperformed the benchmark networks. For example, Fig. 16 shows that 50% of the PDR results for the FuzzOnto network were between 0.3 and 0.4 while the other networks performed lower than 0.34.

### B. VANET Heterogeneous Network

In the VANET heterogeneous network, the simulation scenario considered a multi-lane highway and used the VanetMobiSim 1.1 [47] mobility simulation tool to simulate vehicle mobility. The ns-3 [45] simulator used the mobility traces generated by VanetMobiSim 1.1 to simulate the heterogeneous network. Each vehicle was equipped with a global positioning system (GPS) receiver, and therefore it

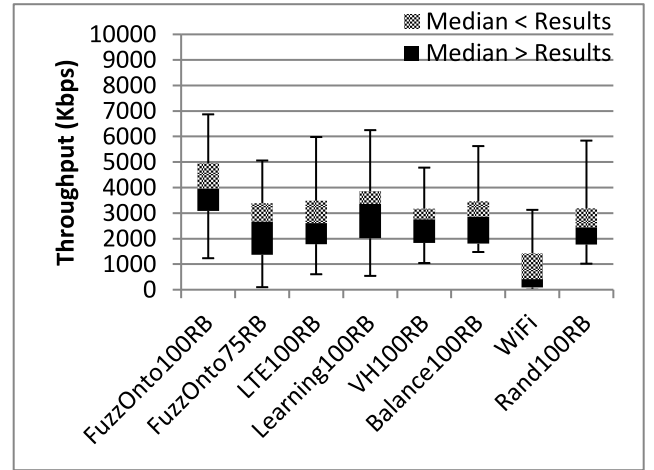


Fig. 12. Average throughput for an urban heterogeneous network with a medium load.

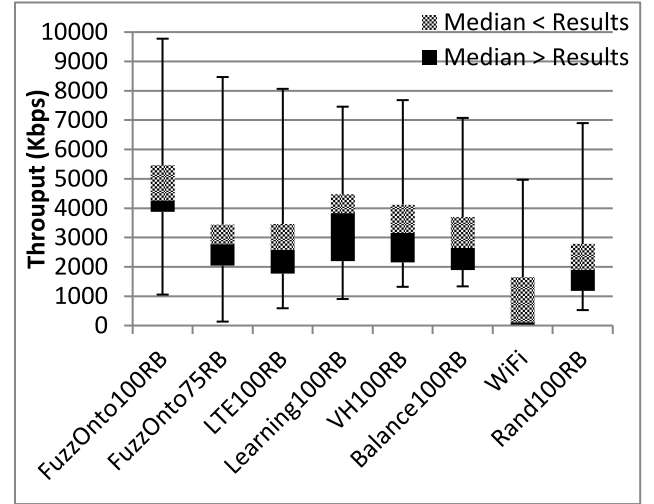


Fig. 13. Average throughput for an urban heterogeneous network with a high load.

was possible to determine the position and velocity of each vehicle.

The proposed cognitive network was compared in terms of throughput and PDR with the same benchmark networks used in the urban heterogeneous network scenario. Figs. 17–22 show the network performance in terms of throughput and PDR.

Similar to the urban heterogeneous network, the FuzzOnto network performed better when the load on the network was high. Fig. 19 shows that the median achieved throughput for FuzzOnto with an LTE bandwidth of 100 RB was around 2.6 Mbps, while the LTE network achieved around 0.5. Even when the FuzzOnto used only 75 RB, it outperformed the LTE network with 100 RB by about 80%. Finally, the FuzzOnto network achieved an average throughput with an increase of more than 40% compared with the other networks. FuzzOnto also achieved a higher PDR compared with the other networks. For example, in Fig. 21, the FuzzOnto network achieved a PDR around 0.45 while the best benchmark network achieved a PDR around 0.29.



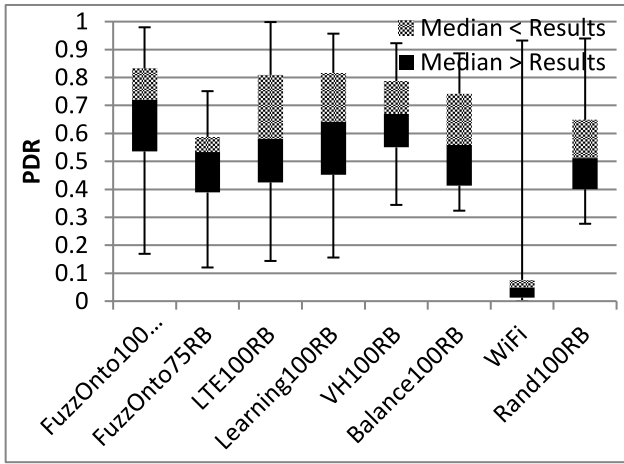


Fig. 14. PDR of an urban heterogeneous network with a low load.

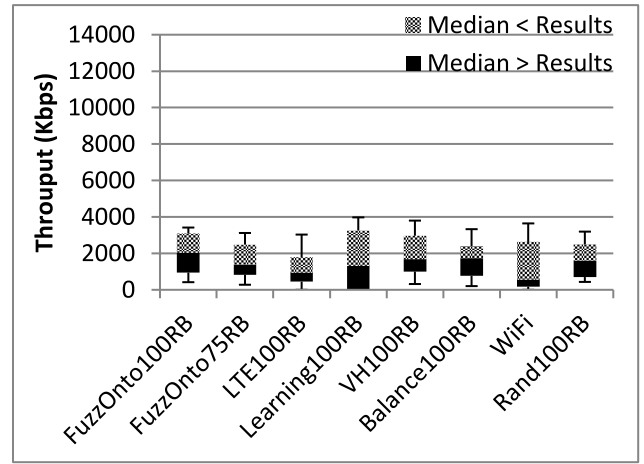


Fig. 17. Average throughput for VANET heterogeneous network with a low load.

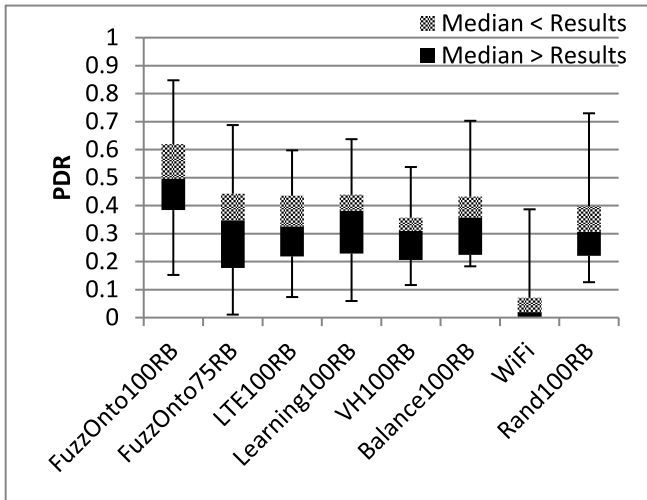


Fig. 15. PDR of an urban heterogeneous network with a medium load.

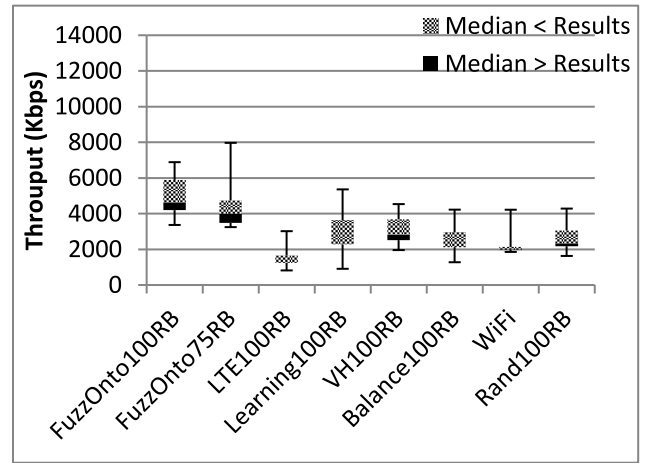


Fig. 18. Average throughput for VANET heterogeneous network with a medium load.

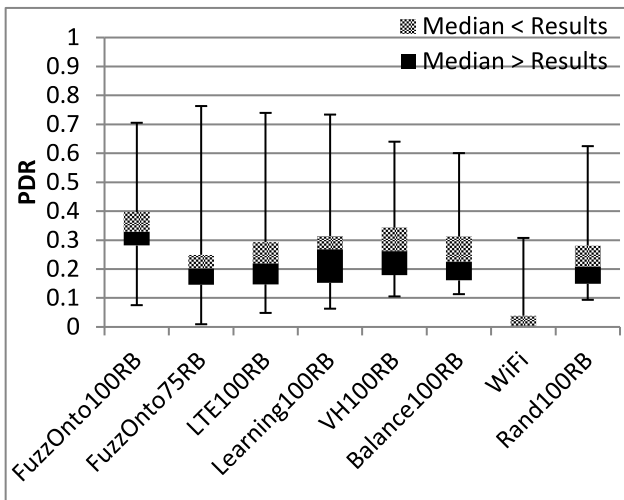


Fig. 16. PDR of an urban heterogeneous network with a high load.

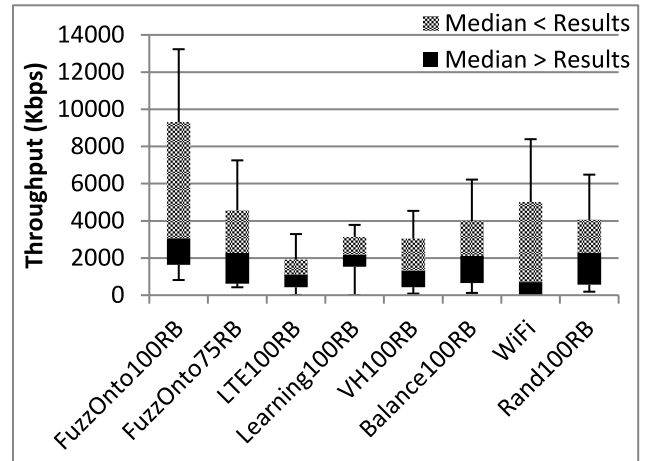


Fig. 19. Average throughput for VANET heterogeneous network with a high load.

Figs. 23 and 24 show the behavior of the network throughput at different loads with different techniques to manage the network.

The results indicate that the proposed algorithm outperforms the benchmark networks, especially when a high load is applied to the network; for example, when the load on the network is low, the average throughput of the Fuzzonto is

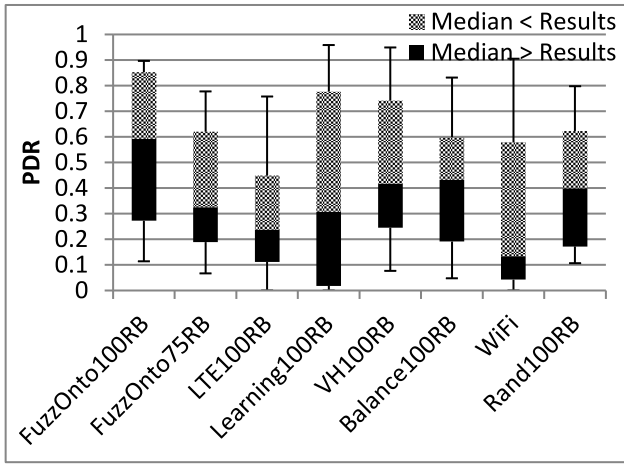


Fig. 20. PDR for VANET heterogeneous network with a low load.

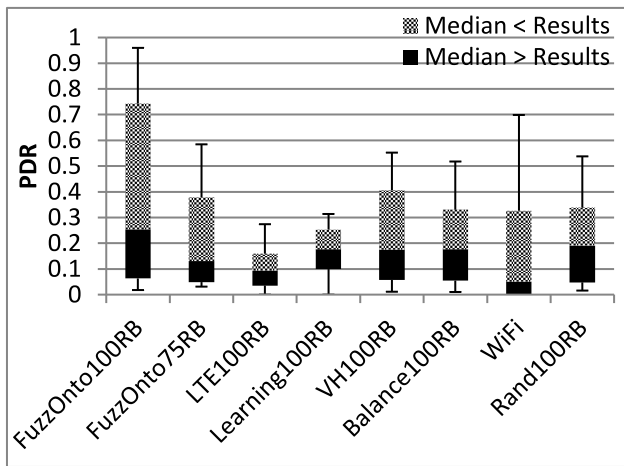


Fig. 21. PDR for VANET heterogeneous network with a medium load.

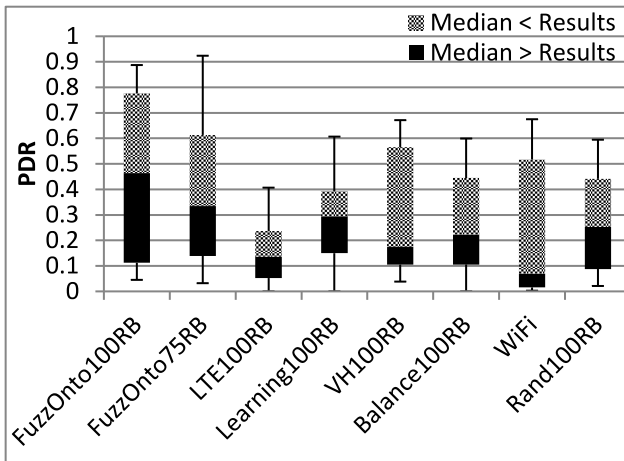


Fig. 22. PDR for VANET heterogeneous network with a high load.

about 2.4 Mb/s with a bandwidth of 100 RB, whereas the LTE-only network with a bandwidth of 100 RB is 2.1 Mb/s (an increase of 13%). The results indicate that the Fuzzonto algorithm adapts very well with the high-load demands in the network compared with the benchmark networks in terms of network throughput. For example, the average network

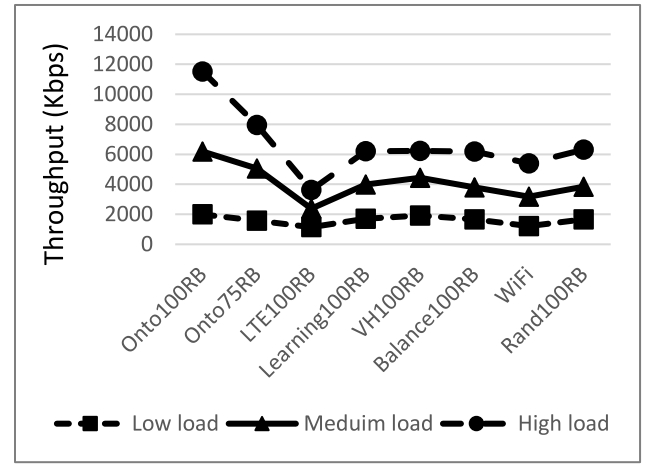


Fig. 23. Average throughput for urban network using different load.

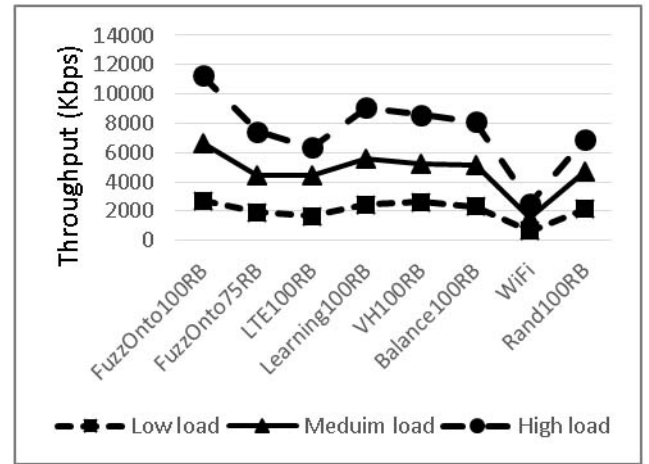


Fig. 24. Average throughput for VANET network using different load.

throughput of Fuzzonto with a bandwidth of 75 RB is around 8 Mbps while LTE, Learning, VH, and Balance achieve 3.9, 6.2, 6.1, 5.9, and 6.1, respectively (an increase of up to 69%).

To verify that the proposed model was significantly improving the network throughput, an analysis of variance (ANOVA) statistical test was performed on each scenario. This test verified that the difference between the results in each scenario was systematic. Equation (5) was used to check whether the results were statistically different.

$$F > F_{\text{Crit}}, \quad (5)$$

where  $F$  is the ANOVA test statistic and  $F_{\text{Crit}}$  is the critical value obtained from the  $F$ -distribution table. Another parameter in the ANOVA test is the probability ( $p$ ) of having improvement where the preferred value is  $< 0.05$ . To verify that the heterogeneous network employing FuzzOnto produced better throughput, Fisher's least significant difference (LSD) test was performed on the results from each network. The average throughput of each network type ( $\text{LTE}_{\text{avr}}$ ,  $\text{FuzzOnto}_{\text{avr}}$ ,  $\text{Rand}_{\text{avr}}$ ,  $\text{VH}_{\text{avr}}$ ,  $\text{Balance}_{\text{avr}}$ , and  $\text{Wi-Fi}_{\text{avr}}$ ) was calculated, and if  $|\text{FuzzOnto}_{\text{avr}} - \text{LTE}_{\text{avr}}| > \text{LSD}$ , then the two averages were statistically different. Table IV shows the ANOVA and LSD results for each scenario.

TABLE IV  
ANOVA AND LSD RESULTS

| Network Scenario  | ANOVA Test |            |             | Throughput Average for the Networks (Kbps) |        |          |        |        |        |         | LSD    |
|-------------------|------------|------------|-------------|--|--------|----------|--------|--------|--------|---------|--------|
|                   | $F$        | $F_{crit}$ | $p$         | FuzzOn to100                               | LTE100 | Learn100 | VH100  | Bal100 | Wi-Fi  | Rand100 |        |
| Urban low load    | 11.5       | 2          | $p < 0.001$ | 2710.4                                     | 2476.3 | 2468.9   | 2643   | 2305.9 | 677    | 2141.3  | 538.5  |
| Urban medium load | 8.83       | 2          | $p < 0.001$ | 3939.1                                     | 2784.8 | 3102.05  | 2593.6 | 2842.  | 854.5  | 2596.9  | 807.73 |
| Urban high load   | 7.79       | 2          | $p < 0.001$ | 4611.4                                     | 2883.3 | 3483.12  | 3329.8 | 2946.5 | 1001.3 | 2152.3  | 1044.1 |
| Vanet low load    | 1.3        | 2          | $p < 0.001$ | 1992.4                                     | 1142.1 | 1707.6   | 1915.1 | 1665.6 | 1222.4 | 1670.5  | 748.22 |
| Vanet medium load | 3.8        | 2          | $p < 0.001$ | 4197                                       | 1236.5 | 2274     | 2514.3 | 2120   | 1962.2 | 2172.6  | 1353   |
| Vanet high load   | 5.1        | 2          | $p < 0.001$ | 5338.1                                     | 1250.2 | 2234.3   | 1789.8 | 2408.1 | 2206.9 | 2465.4  | 1535.2 |

The results of the ANOVA test showed that the throughput results of each network were not obtained by pure chance since  $p$  was smaller than 0.001, and the LSD results proved that the throughput results were statistically different.

## VI. CONCLUSION

This paper introduces a novel cognitive network framework for heterogeneous wireless networks, called FuzzOnto. Its main innovative feature is the way the control of the networks is separated from the infrastructure using middleware that obtains input from the network environment and uses it in the management of various network architectures. Furthermore, this cognitive network framework uses a novel routing decision approach based on two new semantic systems. The first system is a semantic knowledge base in which ontologies and a semantic rule base are used to specify the QoS parameters and different network characteristics. The second system is a semantic inference engine that uses fuzzy logic to create instances of the heterogeneous network ontology in a knowledge base; a fuzzy reasoner is also developed, which uses the knowledge base and the semantic rule base to infer the best action to optimize network performance. The simulation results showed that FuzzOnto outperformed the benchmark networks in two scenarios in which LTE, WMN and VANET were used. The proposed cognitive network framework enhanced network throughput by as much as 70%, even when the LTE network utilized a high bandwidth.

The proposed cognitive network framework has the potential to be extended to support more services and applications using parameters from upper application layers. It could also provide a smart platform for Cyber-Physical Systems and applications such as smart homes, smart cities and smart factories, which might benefit from having heterogeneous networks for their infrastructure.

Another potential research path is the use of high frequency bands, 3–300 GHz as part of 5G networks in the heterogeneous network architectures. This part of the spectrum is not widely utilized, which means that it offers very high data rates but does not suffer from high interference. However, these bands do suffer from higher propagation loss; they also have a poor ability to penetrate objects, and any moisture in the air from rain and fog can significantly reduce the range due to the high

attenuation in the signal. The proposed cognitive framework could utilize these bands in heterogeneous WMN to transmit at a very high data rate by adding new rules to the semantic reasoning system.

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