January - February 2020
ISSN: 0193 - 4120 Page No. 36 - 44

A Hybrid Resource Optimization Technique using Improved Fuzzy Logic Guided Genetic Algorithm for 5G VANETs

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Abstract

Huge amount date, multi-application services and heavy mobile devices can be accommodated by Vehicular networks. Mobile traffic which is increasing rapidly is a major difficulty in vehicular networks. Capacity of network is enhanced by proposing a new paradigm of 5G-enabled vehicular networks in this paper. It also enhances the capability of system's computing. Scalable as well as flexible methods of resource allocation is required by resource of network for supporting user's dynamic requirements of resources and diversified quality of services in 5G driven VANETs.

With connection-centric mind set, recent heterogeneous vehicular networks are designed. In this, irrespective of cell's capacity, static coverage, traffic conditions, resources are allocated in a fixed manner. For a networking controller which is software defined, this work proposes a Hybrid-Improved fuzzy logic guided genetic algorithm (H-FLGA) method. For 5G driven VANETs, problems in optimization of multi-objective resource are solved by this method. In 5G VANETs, five various conditions of network resource optimization is formulated by this proposed method to realize service oriented view.

Based on customers' requirements on type of service, multi-objective weights are optimized by using proposed fuzzy inference system. When compared with GA, multi-objective cost function is reduced by proposed method and it also resulted in less end-to end delay as shown by the results of simulation. A flexible customer-centric network infrastructure can be implemented by using this work which enhances the spectral efficiency

Keywords: *Improved fuzzy logic, next generation VANETs, resource optimization in 5G VANETs, genetic algorithm, 5GVANETs.*

1. Introduction

A vehicular network faces difficulties in communications capacity and computing capability when mobile traffic is explosively increased. As electric vehicle (EV) becomes popular, an explosion of mobile traffic application follows Internet of Things. There are various limitations in vehicular networks: inefficient system management, incapable on-board devices and limited spectrum resource.

Structure of vehicular network is combined with 5G technologies like cloud computing and cloud radio access network (C-RAN) architecture to form a 5G-enabled vehicular network [1]. Advanced mobility management, automated network organization, flexible resource allocation of vehicular network re

January - February 2020
ISSN: 0193 - 4120 Page No. 36 - 44

enhanced by this. With complex process of computing and high data traffic, vehicular service demand can be satisfied effectively.

For delivering broadband services, 5G cellular networks may be utilized by VANETs in future. It may also improve users road safety and traffic. Due to massive diffusion of Internet of Things (IoT) traffic, Machine-to-Machine (M2M) communication may be increased dramatically in coming years. Generation of economic growth and innovations are motivated by this increase in the fields like public transportation, manufacturing, management, healthcare, food and agriculture, media, energy, automotive.

In vehicle environment, high data rate applications are enabled by enticing 5G wireless network due to rapid growth in mobile services [2]. In limited area of coverage, frequency reuse and high spatial are enabled by employing small cells technology in 5G [3].

Centralized RAN is represented by C-RAN. Radio access units are separated from baseband units by C-RAN. BBU pool is formed by migrating BBU to cloud for centralized processing [4]. Traffic load leveraged by allowing functions of network in cloud via virtualization methods. Ability of fibre link connected between data centre and remote radio heads (RRHs) limits exchange of radio signals. In vehicular networks, performance can be enhanced by hierarchical management and decentralized processing.

For transmission of short distance between vehicles and direct mode, Device-to-device (D2D) method can be efficiently used due to influence of surrounding environment [5]. Local links can be established by nearby devices in D2D communication, which enhances capacity of communication [6]. Communication latency can be reduced by frequency reuse [7]. For smooth transmission of data, user is enabled with various sources of wireless signal and they are able switch between sources [8].

Vehicular networks flexibility and performances can be enhanced by network architecture which is defined based on software, cloud computing and processing task. Users can run computation-intensive applications by the use of cloud computing, which cannot be performed by resource-constrained mobile device [9]. For low delay in communication in vehicular networks, Geo-distributed cloud implementation can be used [10].

For best quality of service and performance, SDN architecture manages a hierarchical network formed by RRHs, cloudlets and data centre [11]. Three layers vertical integration architecture is an important advantage of SDN. From underlying devices, control logic are broken [12]. To provide location based services in vehicle applications with fast moving vehicles, it is important to have joint management and cost-efficient resource allocation [13].

In rapid and constant changing problems are solved by Fuzzy logic. In various areas, for the improvement of decision making process in VANET, fuzzy logic is widely used. For VANET, intelligent multi-hop broadcast protocol based on receiver is proposed in this work using fuzzy logic methods.

Efficient allocation of resources, in conventional brute force methods is difficult to tackle with fluctuations in capacity demand and high number of link combination of FC-ZCs [14]. Imprecise data can be handled with tolerance with flexibility by fuzzy logic. Better solutions can be provided by a hybrid method.

Major contributions are listed below,

- For SDN controller, proposed a Hybrid-Fuzzy Logic guided Genetic Algorithm (H-FLGA). It allows the implementation of customer-centric network infrastructure by network providers. For resource optimization in 5G driven VANETs, a hybrid Fuzzy Logic guided GA method utilized.

January - February 2020
ISSN: 0193 - 4120 Page No. 36 - 44

- In 5G driven VANETs, five various conditions of network resource optimization are formulated. Fog Computing-Vehicles (FCVehicles), Fog Computing Cluster-Heads (FC-CHs), Fog Computing BBU Controllers (FC-BBUCs) and Fog Computing-Zone Controllers (FC-ZCs). Allowable connection between FC-BBUCs and FC-ZCs are minimized by this architecture. Idle FC-BBUCs are turned off, in order to make energy efficient and cost effective architecture.
- Based on customers' requirements on type of service, multi-objective weights are optimized by using proposed fuzzy inference system. When compared with GA, multi-objective cost function is reduced by proposed method and it also resulted in less end-to end delayas shown by the results of simulation.
- Idle FC-BBUCs are turned off, in order to make energy efficient and cost effective architecture.

2. Related Work

Due to high density of traffic, intermittently wireless connection, limited coverage area, large mobile vehicles in VANET, it is difficult to implement an efficient and reliable routing protocol.

Li et al. [15] used ant colony algorithm and terminal intersections to implement an adaptive QoS routing. According to delay, packet delivery ratio and connectivity probability optimum route is searched by this algorithm. Al-Kharasani et al. [16] considered various objectives of normalized routing overhead, delay, packet delivery ratio and throughput to implement a particle swarm optimization tuned optimized link state routing protocol for evaluating fitness function.

Latif et al. [17] used multi criteria based mathematical formulation for selecting next forwarding vehicle. It considers, distance between source and actual vehicle, position and direction. Zhang et al. [18] used micro artificial bee colony to implement a multicast routing protocol. Quality of implementation is measured using transmission delay and energy consumption. Miao et al. [19] implemented a routing scheme based on fuzzy logic. Based on time delay and distance, broadcasted packets are forwarded.

Nabil et al. [20] selected a highly stable route and its lifetime is predicted by computing vehicle's neighborslink stability time based on four classes with opposite or same direction of movement with same of different velocity.

Available method addressed major three issues in VANET routing. They are, in the phase of route discovery, route request (RREQ) messages are broadcasted. I results in collision of packet and overhead of control message in highly dense network.

High route breakages are second issue. In the selection route, some affecting criteria are omitted. Due to this high amount of error messages can be introduced with loss of packets. Using fixed lifetime of route is a third issue.

And some are completely based on sender to specify the relay nodes [21], which typically require exchanging periodic hello messages; On the other hand, few works attend the third mentioned dilemma of routing in VANET environment [22].

3. Proposed Methodology

This section proposes a extension of 5G next generation VANET architecture which already proposed [12]. It includes Fog Computing-Vehicles (FCVehicles), Fog Computing Cluster-Heads (FC-CHs), Fog Computing BBU Controllers (FC-BBUCs) and Fog Computing-Zone Controllers (FC-ZCs). Allowable connection between FC-BBUCs and FC-ZCs are minimized by this architecture. Idle FC-BBUCs are turned off, in order to make energy efficient and cost effective architecture. In 5G driven VANETs, five various conditions of network resource optimization are formulated.

January - February 2020
ISSN: 0193 - 4120 Page No. 36 - 44

1.1.5G-Enabled Vehicular Network

Rapidly increasing need of mobility and high data rate can be satisfied with revolution in current vehicular network by 5G wireless communications. There are three major features of proposed 5G-enabled vehicular network. They are, architecture of SDN for managing and controlling system, processing of application by geo-distributed cloudlets, resilient communication through D2D technology and enhanced C-RAN.

Vehicular network is enhanced by integrated framework which is having advantage of resource allocation in a flexible manner, efficient processing abilities, and robust network of communication. Cost reduction and saving of energy motivates this framework of system. Proposed architecture of 5G-enabled vehicular network is represented in figure 1.

Vehicles can asses base station and make a communication with cloudlets in 5G communications. OBUs handle processing of data and communication between vehicles in traditional methods. Average speed of vehicle and density of vehicle affected transmission of 802.11b/g protocol [20] [21].

With respect to mobility, scalability, reliability, delay and throughput, better performance is shown by 5G cellular network. For low mobility, peak data rate is 10 Gb/s and for high mobility, peak data rate is 1 Gb/s in 5G network. For moving vehicles, about less than 1 ms latency is supported by this. High speed trains (350 – 500 km/h) are also served by this [22] [23]. D2D communication and EC-RAN are the interested 5G technologies in vehicular network.

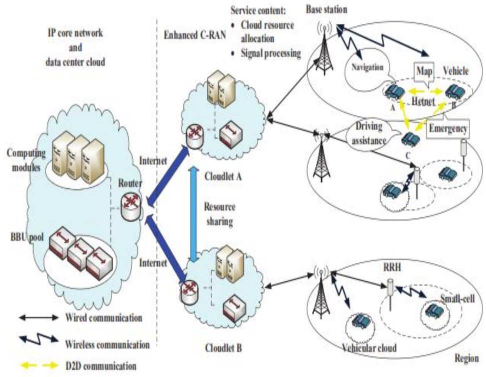

Fig. 1.5G-enabled vehicular network architecture

Minimize the Number of FC-BBUCs (Min-BBUC): Minimization of number of FC-BBUCs serving FC-ZCs is a major objective of this problem. Resources are requested by FC-ZCs. Objective function is given by

$$\min C_{nBBUC} = \sum_{i=1}^{nBBUC} C_{BBUC_i} Y_i$$

Where, number of FC-BBUCs in pool is represented as nBBUC, ith element is represented as $C_{BBU\,C_i}$ and it has a value equal to total available capacity of FC-BBUCi.

Minimize Delay (Min-Delay): Connecting FC-ZCs close to possible pool location of BBUC caused delay in large manner. Minimization of such delay is a major objective in this case. Objective function is given by

$$\min C_{Delay} = \sum_{i=1}^{nBBUC} \sum_{j=1}^{nZC} Cost_{i,j} Z_{ij}$$

wherenBBUC is number of BBUCs in pool, $\mathrm{Cost}_{i,j}$isthe link cost for linking ZCs j and BBUC_iin the cost matrix$\mathrm{Cost}_{i,j}$.

Capacity Load Balance (Cap-LB)): In each BBUC pool, traffic load is balanced by Cap-LB algorithm. Every BBUC pool's traffic load is available at every time and SDN controller updates it. Possible BBUC pool connection's traffic load information is contained by controller before decision evaluation. Objective function is given by

January - February 2020
ISSN: 0193 - 4120 Page No. 36 - 44

$$\min C_{capL} = \frac{1}{nBBUC}\sqrt{\sum_{i=1}^{nBBUC}(D-D_i)^2}$$

$D_i = \sum_{j=1}^{nZC} Z_{ij} C_{ZC_j}$ and $D = \frac{1}{nBBUC}\sum_{i=1}^{nBBUC} D_i$, Where D_i is the ithe element indicating the totalload demand in $BBUC_i$.

Number of FC-ZCs per BBUC Balance Algorithm

(FC-ZC-per-BBUC-Bal): Balancing number of connections serving FC-ZCs to BBUCs is a major objective. Resources are requested by FC-ZCs via FC-ZC-per-BBUC-Bal algorithm. The objective function is given by

$$\min C_{ZC_{perBBUC}} = \frac{1}{nBBUC}\sqrt{\sum_{i=1}^{nBBUC}(N-N_i)^2}$$

$N_i = \sum_{j=1}^{nZC} Z_{ij}$ and $N = \frac{1}{nBBUC}\sum_{i=1}^{nBBUC} N_i$

Where, total number of FC-ZCs connected to$BBUC_i$ is indicated by N_i, which indicates ith element in total connections vector N. Reduction of total connections vector N's standard deviation is a major objective. Under ideal conditions, value of objective function is zero, if all BBUCs has same number of connection.

Constant Traffic Load (CTL))

In each BBUC pool, constant traffic profile is forced by CTL algorithm. Traffic peaks are avoided using three FC-ZCs types. They are Mixed FC-ZCs, Commercial FC-ZCs and Residential FC-ZCs. Following expresses the objective function,

$$C_{CTL} = \sum_{i=1}^{nBBUC} BTD_i$$

Where BTD_i standard deviation of Rfor $i \in \{1, 2, \ldots, nBBUC\}$, $R_i$column vector which has total demand in BBUC with each row corresponding to a duration interval. BTD iiis the ith value indicating the standard deviation of variation of total demand in BBUC.

Multi-Objective Optimization

Algebraic sum of post-operated individual objective function produces Multi-objective function. It will have a minimum value of 0 and maximum value of 1. Every individual objective functions are normalized by a factor which are described in previous section, to create impartial multi-objective function. Equal importance is given to all objective function by assigning unit weight to all objective functions. Every link cost, a binary link matrix used to indicate allowable connections between FC-ZCs and BBUCs, FC-ZCs time-series demands, BBUCs link capacity are the problems of input.

1.2.Hybrid-fuzzy logic guided genetic Algorithm (H-FLGA)

In order to solve problems in multi-objective optimization, a Hybrid-Fuzzy Logic guided Genetic Algorithm (H-FLGA) method for SDN controller is proposed. Between FC-ZCs and BBUCs, more accurate connection arrangement is assigned by combining various objectives. Fuzzy Inference System is used for weighting and optimizing various options based on customers requirement on Type of Service (ToS). Optimum solution is given by using GA after FIS.

Proposed algorithms flowchart is shown in figure 6.There are two inputs in fuzzy system. They are value (Value) and Type of service (ToS). Customer's requirement is denoted as ToS. It is based on three parameters namely, Cost, Delay, throughput. For Multi-objectives optimized weights, coefficients ω are prioritized by FIS output. Hence, $\omega = f(Tos, Value)$ where $ToS = \{Delay(D), Throughput(T), Cost(C)\}$ and Value= $\{0, 1\}$. Output will lies between [0,1]. For output and input variables, Gaussian membership function is selected.

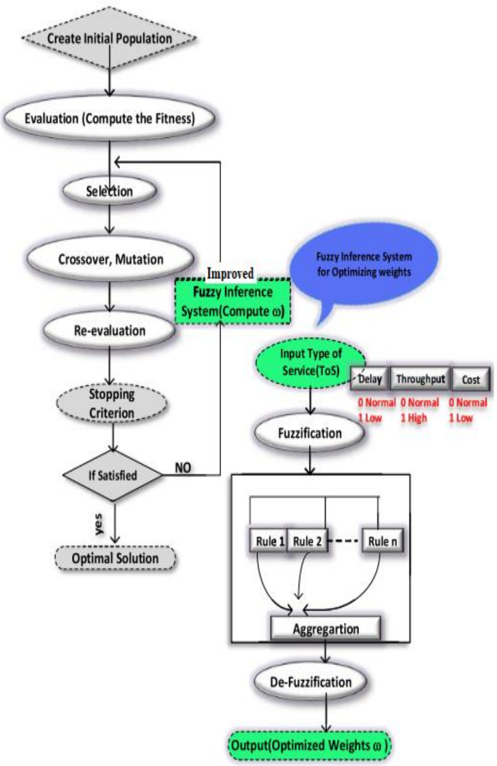

Fig.2. Flowchart of Hybrid-Improved Fuzzy Logic Guided Genetic Algorithm (H-IFLGA)

1.3.An Improved Fuzzy Guided Genetic Algorithm

An Improved fuzzy guided genetic algorithm is similar to the FGA except that this has the ability to meet the dynamic consumer requests and services. The construction for the fuzzy engine is shown in the Fig. 3. With mutation and crossover controller, a fuzzy engine is built. Fuzzy engine receives two inputs Δf and d where Δf is the average fitness difference and d is the bit difference between the all pairs of individuals in the population

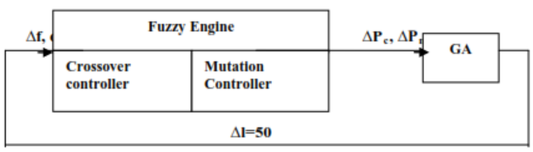

Fig.3. Fuzzy Engine

Bit difference is calculated as:

$$d = \frac{1}{(N(N-1)/2)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \sum_{k=1}^{C} \frac{\Delta(pop_{ik}, pop_{jk})}{C}$$

Where, population size is represented as N and Genome Length is represented as C. Here pop_{ik} and pop_{jk} are the kth bit value of ith individual and kth bit value of j□h individual respectively. If pop_{ik}, pop_{jk} have same value then $\Delta(\mathrm{pop}_{ik}, \mathrm{pop}_{jk}) = 0$ else $\Delta(\mathrm{pop}_{ik}, \mathrm{pop}_{jk})$ returns 1.The fuzzy engine in turn produces two outputs, rate of crossover ΔP_c and rate of mutation (ΔP_m) and sends to GA. GA uses the updated crossover and mutation rates continues its execution for 50 generations. This process continues until the exact solution is reached. Fuzzy engine has three parts Fuzzification, Fuzzy rules, Defuzzification.

Rules: Following shows ω_i rules,

$r1$=if ToS is D with zero value, then ω_1 =0;

r2 = if ToS is D with non-zero value, then ω_1=0;

r3 =if ToS is T with zero value, then ω_1 will be medium;

r4 = if ToS is T with non-zero value, then $\omega_1$will be high;

r5 =if ToS is C with zero value, then ω_1 will be medium;

r6 =if ToS is C with non-zero value, then $\omega_1$will be high;

Likewise rules for $\omega_2, \omega_3, \omega_4$and ω_5 are defined.After the application of the Improved Fuzzy Inference System, GA's revaluation part is executed. Using multi-objective function with new weights, population's fitness value are computed. H-IFLGA is given in Table.1.

Table.1.Algorithm of H-FLGA

Input:FC-ZCs demand, BBUC link capacity, critical demands threshold, Type of Service (ToS) and priority Value
Output: Optimized weights, multi-objectives (
Methods: evalfis(), H-IFLGA()

January - February 2020
ISSN: 0193 - 4120 Page No. 36 - 44

H-IFLGA:

(1) max generation number $G_{MAX}$is selected and cyclesize C ,set t = 0,

(2) Initialize randomly population

(3) In population, every individuals fitness is computed.

(4) In

Population, current best individual is extracted and saved.

(5) if $t \leq G_{MAX}$Stop,

else set $t = t + 1$ and go to step (5)

(6) Mutation, crossover and selection are applied.

(7) Go to step (2), if $mod(t, C) \neq 0$, else new weights are computed by calling Fuzzy Inference System (FIS)

(8) end

4. Simulation Results and Discussions

MATLAB 2017b is used for implementing proposed algorithm. Fuzzy logic rules are implemented using evalfis(). Proposed H-IFLGA algorithm performance in optimizing multi-objective function is compared with GA. Multi-objective cost function is used as an evaluation measure. This value must ranges between 0 to 5. Various objectives weights in [17] are optimized by test results. On various aspects of network, five various resource optimization conditions are focused and related indirectly with these objectives.

Table.2. Simulation Parameters

Simulation Parameter	Value
Maximum capacity of BBUC pool	$100MHz$
Maximum Fronthaul distance	$40KM$
Number of Vehicles	50 *to* 300
Transmission range of vehicles	up to $300m$
Speed of Vehicles	between $10m/s$ and $30m/s$
MAC protocol	IEEE 802.11($11Mbps$)
Mobility Model	Manhattan grid ($2500m \times 2500m$)
Packet size	$512bytes$
Population size	2000
Tolerance for objective function	$1e-8$
Crossover Operator	single (or multi) point

1.4.Multi-objective function value results

Fig. 4 shows the variation of the objective function for the optimized parameters using the H-IFLGA approach, H-FLGA and GA. The population size of 1000 is used for each generation and the number of generations is increased from 10 to 50 with an increment of 10. It is observed that increasing number of generations optimizes the value of the objective function however; beyond 10 generations it is observed that value of objective function remains more or less the same.

Multi-objective function's best score is optimized to 10.32 using H-FLGA cost function value. It should lies between 0 to 5 and it cannot be optimized by GA and H-FLGA. Multi-objective cost function result can be improved by using a hybrid H-IFLGA for optimizing multi-objective function's weights.

Using H-IFLGA, optimized a multi-objective cost function to a value of 2.2. Experimental results are shown in figure 7. With fixed values of weights ω_i, problems in multi-objective optimization is solved. All cost functions are given with equal importance and assigned a value of one (C1 to C5).

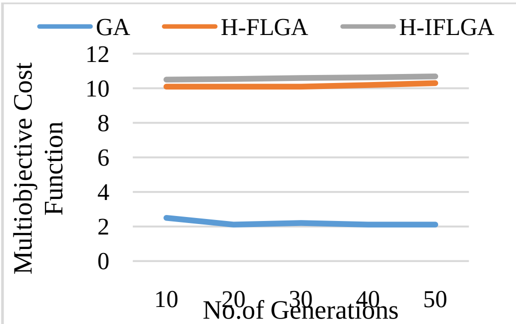

Fig. 4. Variation of multi-objective function value for different numbers of generations

1.5.End-to-end delay comparison results

End-to End delay comparison vehicles of GA, H-FLGA and H-IFLGA methods are shown in figure 5. 40kmis used as maximum front-haul distance. With varying speed, from 50 to 300, count of the vehicle is increased. Proposed HFLGA produced high value of delay. Confidence of an interval of 95% is indicated using vertical markers in every point of graph. When compared with H-FLGA and GA, wide level of confidence is exhibited by this. High variation of delay is indicated by this. GA results in maximum value of delay as 0.113s with ω2 set to 1, H-FLGA results in maximum delay of 0.171s. Proposed H-IFLGA has produced a low value of delay as 0.062s.

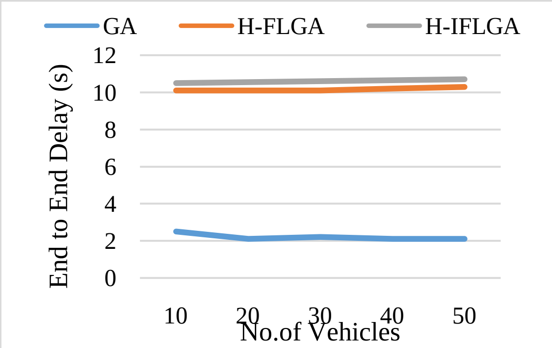

Fig. 4. End-to-End Delay

5. Conclusion and Future work

In 5g operated VANETs, for SDN controller, optimum allocation of resource is done by proposing a hybrid Improved Fuzzy Logic guided Genetic Algorithm (H-IFLGA). Problems of multi-objective optimization are solved using this method. Various objectives are combined in this method. Multiple objective weights are optimized by proposed FIS. Connections between FC-ZCs and BBUCs are optimized by using Genetic Algorithm with optimized weights. A flexible customer-centric network infrastructure can be implemented by using this work which enhances the spectral efficiency.

Service providers are supported with energy efficient optimization. In overall system, without any diverse effect, BBUC's may be turned off, which reduces OpEx. In future, ultra dense networks can be used to implement proposed method for allocation of resources and offloading. Mininet and Open Flow can be used test the proposed method.

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