Controlling Traffic in Internet of Vehicles Using Energy Aware Optimized Intelligent Transport System Using Red deer algorithm with New FNN Method

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ABSTRACT

Networks deployed in Internet of Vehicle (IoV) has an eminent rolein message exchanging in addition to associated services or application. The advancement in Intelligent transportation system has eased existing traffic conditions which has gained attention due to smart cities besidesIoVsinvolved in Internet of Things up gradation. On the basis of traffic intensity environment, proficient establishment besides consistent intercommunication routes amid vehicular node is greatly necessitated. One among proposed methodology namely fuzzy logic based traffic intensity calculation function is utilized previously for mitigating those issues for huge traffic modelling. Conversely, membership function selection through iterative methodology is regarded as a time consuming task. On the basis of on Takagi–Sugeno (TS) model with intelligent water drop algorithm (TSFNN-IWD),a novel fuzzy neural network (FNN) is presented for precise traffic intensity assessment, currently IWD is exploited for optimal membership value selection. The optimal route path selection outcome is extemporized on the basis of Red deer algorithm (EARD) with TSFNN-IWD through an intelligent transportation system establishment with energy-aware routing which is entitled as EARD-TSFNN-IWD-IoV for transmission range adapting intensity in local traffic concern. The various performance metrics such as throughput, packet delivery, drop ratio in addition to average end-to-end delay are assessed for proposed EARD-TSFNN-IWD-IoV protocol and validated the superiority of the proposed method in contradiction to 0prevailing EACOFNNIoV besides ELHACOGFNNGAIoV protocols.

Keywords:

Internet of Vehicle, Fuzzy logic based traffic intensity, fuzzy neural network (FNN), Takagi–Sugeno (TS) model and Red deer algorithm

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1. INTRODUCTION

Recent technology advancement acquired progression in transportation field also, explicitly in vehicular transportation [1]. The rapid development of transportation technologies has transformed transportation system into intelligent transportation system (ITS) [2]. VANET(vehicular ad hoc network) is one amid the eminent technology which supports in modification of vehicles to get connected through wireless router for enable inter-vehicular communication by means of Internet of Vehicles (IoV) encompassing both vehicular networking, as well as vehicular intelligence [3] for ITSes. IoV is considered as an intelligent communication link amid vehicles in addition public networks for instance vehicle-to-vehicle, vehicle-to-road, besides vehicle-to-human communications, the systems connections are done electronically plus communication through mobile Internet. IoV greatly utilizes Dedicated short-range communication (DSRC) devices, operating in 5.9 GHz band [4] and communication range amid the devices is around 1000 m.

The accident prevention and/or road traffic congestion are chiefly achieved through collection or information sharing about vehicle, road infrastructure, or vehicle user, besides this information processing for guiding or supervise vehicles proficiently. These are the points considered as IoV main objectives to have a pleasant driving experience considering the drivers/passengers safety. The transportation sustainability maintenance is yet an necessitated and challenging factor regardless of the vehicular transportation progression. The road traffic safety is another vital factor which in turn depends on go-green transportation management along with proficient transportation planning systems apart from transportation sustainability. Various reasons are involved for road accidents, such as, animal or pedestrian crossing, collisions due to congestion, environmental disasters, insecure lane variations, incorrect turning, besides distracted driving. Hence it is mandatory to guarantee vehicular transportation sustainability through implementation of an effective intelligent transportation planning system for enhancing road safety in addition obtaining a more eco-friendly environment.

Traffic congestion is regarded as a severe concern in large cities over the last eras which have a significant part inhumans daily lives along with stable economic in addition to societal progress .It may also leads to air pollution up surging , travel time, and economic losses. There are various initiatives taken by the government for traffic congestion monitoring and resolving since it is regarded to be a challenging and complex task. Traffic congestion prediction is also another challenging task. The dynamic and interrelated characteristics influence the traffic congestion complexity. The traffic congestion propogation takes place from a congested road segment to neighboring road segments. The completely traffic congestion automatic analysis is another difficult task to be acquired due to the complexities involved.

This research concentrates on utilizing vehicular communications for traffic signal control since vehicular communication functionality is regarded as IoV vital abilities and possess numerous benefits such as lightweight computing, no supplementary operational (installation besides maintenance) cost, resilience to lighting condition (i.e., might operate all day) plus resilience to harsh road condition (e.g., might operate to a definite degree even in a non-line-of-sight atmosphere). The description of various approaches utilized in this research are

- Cluster based Energy-aware routing scheme based on Red deer algorithm (EARD) is initially exploited for optimal route path selection outcome enhancement.
- A New fuzzy neural network based on Takagi–Sugeno (T–S) model with intelligent water drop algorithm (TSFNN-IWD) is greatly utilized for accurate traffic intensity measurement, at this point IWD is involved for optimal membership valueselction.
- Taffic intensity assessment is done through various parameters such as vehicle movement speed (VMS), number of vehicles currently moving on a road (NV), direction of arrival, Vehicle speeds , flows for one direction of travelin addition toDensity of vehicle (DV).
- These two algorithms together denoted as ARD- TSFNN-IWD-IoV for effective traffic control system throughIoV technology besides transmission range adaptation regarding intensity in local traffic.

The research work structure is arranged as follows: Section 2 outlines the traffic congestion associated works in vehicle network. Recommended approach of EARD-TSFNN-IWD-IoV is elucidated in section 3. Recommended technique implementation alongside with the outcomes attainedin addition to simulation outcomes elucidation is given in section 4.. As a final point, Section 5 affords conclusion directions for future work.

2. RELATED WORK

Abbas et al., [5] realized enriched vehicle-to-vehicle as well as vehicle-to-infrastructure communication through designing a infrastructure-assisted hybrid road-aware routing protocol. The peculiarity is that there recognised a link amid path duration besides fundamental design parameters like vehicular velocity, density, hop count and transmission range. Though there are many researches in this regard, a definite analytical model for IoV is absent in the collected works.

Gasmi et al., [6] extemporised Zone Routing Protocol for establishing for designing a Stable Link based Zone Routing Protocol (SL-ZRP) for link stability creation in IoV applications exploitingQoS function on the basis of speed, destination and delay. The stable routes are also obtained which in turn mitigates response time in addition to network overhead.The SL-ZRP performance is assessed with the help of several performance metrics.

Shelke et al., [7] suggested an approach in which monitoring of trafficinformation is done through sensor nodes in addition transmitted it to a Dynamic Traffic Management Center (DTMC). Road segment priority is determined in terms of critical, high, medium and low through fuzzy logic. Congestion -aware routing algorithm is greatly utilized for packet transmission to DTMC.

Ahmed et al., [8] suggested an approach for non-equipped vehicles since it affects traffic congestion primarily .A novel route suggestion protocol is completed for an optimal congestion aware route in network. Congestion index formulation laterally with driving distraction aspects are performed for both Equipped and non-equipped vehicles.

Thakur &Malekian [9] offered an investigation in communication channel through analysing IoVestablished system for road safety besides traffic management applications. Most appropriate wireless communication technologies for the communication channels in an IoV system are obtained through evaluation of wireless communication technologies performance.

Aadil et al., [10] concentrated IoV topology stability in a dynamic environment. The traffic density forms the framework for developing metaheuristic dragonfly-based clustering algorithm CAVDO for the purpose of cluster-based packet route optimization for obtaining stable topology. Also transmission range adaptation is attained through combination of mobility aware dynamic transmission range algorithm (MA-DTR) with CAVDO. To validate the performance, it is contrasted with progressive baseline techniques ant colony optimization (ACO) besides comprehensive learning particle swarm optimization (CLPSO).

Abbas et al., [11] suggested a methodology for flexibility and scalability management through an optimal routing protocol for internet of vehicles with diminished overhead. The highly dynamic networks are managed by fragmenting data plane from control plane and thereby achieving evolving network standardconsolidation termed as software defined networking in IoV.

Ting et al., [12] accomplished a congestion warning technique on the basis of IoV besides complex networks community discovery. Fast Newman (FN) algorithm is utilized for communitiesdiscovery in this complex network as well as creation of congestion warnings on the basis of communities selection through scale and density. Traffic tendency can be detected through this methodology aggregation besides afford warnings before congestion occurs.

Kamble&Kounte [13] utilized manifold parameters such as hard delay constraints, speed offered through GSP vehicle trajectory for traffic congestion identification by ML methodology. Three datasets are mainly involved namely training set, prediction set, and road sector data frame for prediction of traffic speed through Gaussian process in ML. Live traffic prediction in real-time, future traffic prediction in addition short-term traffic prediction on latest observation besides historical data is also achieved through ML.

Chen& Chang [14] suggested an approach for global throughput in addition to travel time optimization for manifold intersections by cooperative traffic control framework. The analyses of their joint passing rates are necessitated in adjacent intersections in addition attempting to maximize number of vehicles traveling through road network. This method greatly achieves fairness for each road segment in addition torecognize green wave concept for arterial roads.

Lin et al., [15] attained traffic flow control through traffic congestion reduction by an algorithm namely social vehicle route selection (SVRS). The historical as well as current driving information are involved for designing a social clustering method for SIoV.

The literature review infers that latency is not concentrated in attainment of traffic information to the sink node due to congestion. It also strongly conveys that it greatly necessitates robust, feasible in addition cost-effective framework for integrating dynamic traffic signal management in addition to congestion-aware routing strategy for transmission delay reductionfor emergency messages transmission for effective emergency vehicle management besidesupsurge network lifetime.

3. PROPOSED METHODOLOGY

Lively Hovering Ant Colony Optimization is greatly utilized in this research for extemporising traffic situation proficiently in IOV and best path prediction is given to the destination. The various traffic factors such as vehicle moving speed, cars arrival rate are taken into account for this work. LHACO Local pheromone updating while detecting optimum traffic factors direction amid sources to destination is achieved through route selection system based Gaussian fuzzy neural network with Genetic Algorithm. Genetic algorithm is chiefly utilized for auto-tuning technique for the fuzzy neural network. Fuzzy model minimal and optimal structure is constructed through this new tuning method. The suggested methodology block diagram is shown in Fig 1 where ELHACOGFNNGAIoV and the GFNNGA collectively work for choosing most favorable route LHACO system.

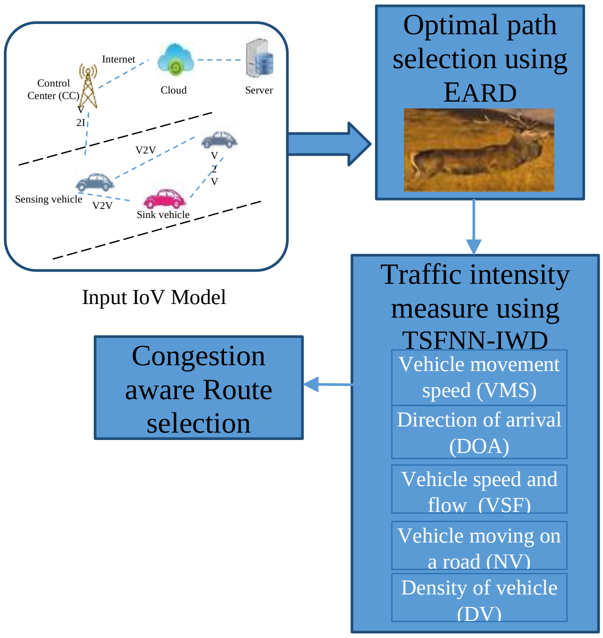

Fig.1.Block diagram of proposed EARD-TSFNN-IWD-IoVsystem

3.1.IoV System Model

An IoV assisted network architecture is exploited in this research for collecting and diffusing traffic information efficiency improvement. Global information for obtaining final decisions is necessitated for top-level urban traffic management. It requires sensors, control center and communication units to be equipped for satisfying certain tasks as depicted in fig 1. On the basis of their missions, it also demands equipping of GPS, radar, cameras, and so on apart from various classic sensors. Each part collaboration is mainly meant for control and management units. The traffic information integration as well asforwarding command messages is achieved through powerful data fusion of control Center (CC).

A graph $G = (X, E)$ is defined by the set X of its vertices besides set E of its Edges. Let $X = \{x_i | \ i = 1, \dots, N\}$ be used for Nvehicles set.

The restricted sensing scope and computational capability of every vehicle makes aggregation from every sensing vehicle to be done through sink vehicles (gateways) for information gathering from other nodes in ITS and forwarding traffic information to ontrolcenter. The broadcasting of traffic control messages from the control center to the other vehicles is accomplished through these sink vehicles. Prevention of Heavy traffic formation and accidents are achieved with the suggested IoV based traffic management. This research work is carried out in Vellore district, Tamil Nadu, India where numbers of small maps are acquired through segmentation of street maps as in [6]. Also optimal route is obtained by applying EARD algorithm on each map. Furthermore TSFNN-IWDbased traffic intensity calculation function is suggested on the base of vehicle movement speed, number of vehicles currently moving on a road (NV), Density of vehicle (DV), direction of arrival, Vehicle speeds and flows for one direction of travel parameters.

3.2.Map Segmented Structure

Usually there exhibits different traffic-flow levels besides traffic congestion by road network segments in case of high-traffic-flow road segments. As soon as vehicle number attains road segment volume, traffic congestion begins at a particular road segment. Subsequently, propagation of traffic congestion starts from a congested road segment to neighboring road segments. Historical Vehicle ID (VID) data is exploited for road network traffic-flow levels investigation through which local traffic congestion prediction is attained. Red legend as the location symbol is used in every VID device. VID device should be positioned at an appropriate position for ensuring that traffic flows on its own predefined road observation is done through every VID device as well as this is regarded as . Taiwan's government recommendation for evading redundant data in traffic observation, wasted deployment along with maintenance expenses. Time Recording is accomplished through date-time field. The origin-destination traffic congestion service is attained through vehicle's current speed in amalgamation with vehicle location

3.3.Energy Aware routing scheme based on Red Deer algorithm (EARD)

FathollahiFard and Hajiaghaei-Keshteli [10] suggested recent metaheuristics initially through balancing amid intensification and diversification by providing user opportunity. Red Deer's characteristics in breeding season is exploited besides simulating their main behaviors in this particular time of year. A subspecies of Red Deer namely Scottish Red Deer (CervusElaphusScoticus) which lives in British Isles is regarded for this work. The loud roar is done recurrently in the course of breeding season by the males besides high to a low roaring rate is given by females. The male territories have to be increased by the males as well as the number of hinds in their harems and hence course of fight is inevitable. The handy hind mating is desired since there is no option of male possessing territory and harem. In a nutshell, RDAbegins with an initial population, termed Red Deers (RD). They are separated into two types: hinds as well as male RDs. Besides, a harem is a female RDsgroup ,in addition male RDs competition for obtaining harem with more hinds by roaring in addition to fighting, and their mating behavior is the foundation of the suggested evolutionary algorithm. The detailed stages are elucidated below.

Initialization: An optimized array is regarded for this work as alike to other meta heuristics. The array terminology is termed as "chromosome" in case of GA, whereas in RDA "Red Deer" is utilized for this array. Consequently, Red Deer (RD) is the solutioncounterpart . It is to be noted that ''Red Deer'' relates to a feasible solution X inside the solution space. Hence, red deer is a solutioncounterpart and this solution dimensionality X isN_{var}. In an N_{var}–dimensional optimization problem, a Red Deer is a$1 \times N_{var}$ array. This array definition is given by:

$$RD = [X_1, X_2, X_3, \dots, X_{N_{var}}] \quad (1)$$

Also, function evaluation for each RDs isas follows:

$$Value\ of\ function = f(RD) \quad (2)$$

The algorithm is initiated through generating the initial population of size N_p is. Some of the best RDs are nominated to N_{male} and the remaining of to N_{hind}.

Roaring male RDs: Roaring is one of the main step involved in the process for their grace up surging. The roaring process might be successful or failure which occurs naturally.Good solutions neighbours are obtained in solution space (male RDs) as well as if the neighborsobjective functions are improved than good solutions, they substitute with the prior ones. In circumstances, each male RD is allowedfor their position change.

Selecting γ percent of best males as commanders: There exist many variations amid male RDs naturally. Out of those few may be further powerful, more attractive, or more successful in territory expanding than the others. Accordingly, RDs are alienated into two types: commanders in addition stags, and computation of number of commander$N_{commander}$ males is as trails:

$$N_{Commander} = round\{\gamma . N_{male}\} \quad (3)$$

where$N_{Commander}$ denotes number of males that form the haremswho are harems commanders . It is noted that c representsalgorithm modelinitial value and it lies between zero and one. Lastly, number of stagsestimation is done through:

$$\mathrm{N_{stag}} = \mathrm{N_{male}} - \mathrm{N_{Commander}} \quad (4)$$

where$\mathrm{N_{stag}}$notates number of stags in regard to male population.

Fighting between commanders and stags: There occurs commander fight with stagsrandomly.In solution space, a commander besides a stag are move toward to each other. Consequently, two new solutions are attainedin additionsubstituted the commander through the improved solution, i.e. has improved objective function amid four solutions (commander, stag, in addition to two new solutions acquiredsubsequently approaching). The objective function computed on the basis of vehicle noderesidual energy is revealed:

The assessment of node energy is done in terms of a joule (J).The energy$E$ computation is as follows,

$$energy\ (E) = p * t \quad (5)$$

Where $p$represents power in watts and t representstime in seconds (Sec). After that, the degradation of each sensor nodes energy happensand left over node energy (i.e.residual energy (RE)) act as objective function $f$for Red Deer algorithm are computed as follows

$$objective\ function \rightarrow f(RE) = TE - CE \quad (6)$$

Where TE denotes total energy and CE signifies vehicle nodes consumed energy.

Forming harems: Currently, harems formation is attained. A harem is a group of hinds that a male commander seized them. The number of hinds in haremsare influenced by male commanders power. Hinds amid commanders are separated proportionally for harems forming as follows:

$$V_N = P_n - \max_i\{v_i\} * f(RE) \quad (7)$$

where$P_n$notates$n$th commander power and V_N is its normalized value. Every male commander normalized power is computed through all commanders normalized powers:

$$P_n = \left| \frac{V_n}{\sum_{i=1}^{N_{commander}} v_i} \right| \quad (8)$$

In other view, the male commander normalized power is hinds portion that should be obsessedthrough that male. Then number of hinds of a harem will be:

$$N.harem_n = round\{P_n \times N_{hind}\} \quad (9)$$

where$N.harem_n$notates number of hinds in nth harem and N_{hind}denotes number of all hinds. The hinds divisionto each male commander is done through selecting user randomly $N.harem_n$ of hinds. These hinds alongside with the male will form nth harem.

Mating commander with α percent of hinds in his harem: Naturally deer mating happens like other species.. This action is completedthrough commander besides$\propto$percent of hinds in his harem are the parents.

$$N.harem_n^{mate} = round\{\propto\times N.harem_n\} \quad (10)$$

where$N.harem_n^{mate}$denotes number of hinds of nth harem that mate with their commander. In solution space, user arbitrarilyselects$N.harem_n^{mate}$ of $N.harem_n\}$.

Mating commander with β percent of hinds in another harem: Aarbitrary harem selection is done (name it k) and let male commander mate with β percent of hinds in this harem. In circumstance, the commander attacks to another harem for expanding his territory. The number of hinds computation in the harem which mate with the commander is as follows:

$$N.harem_k^{mate} = round\{\beta \times N.harem_k\} \quad (11)$$

where$N.harem_k^{mate}$signifies number of hinds in kth harem which mate with the commander.

Mating stag with the nearest hind: This stage involved every stag mating with its closest hind. In breeding season, male RDs desire to track handy hind. This hind may perhaps his preferred hind amidaltogether hinds deprived ofreflection of harem territories, i.e. this hind maybe in his harem or habituates in another harem. User allowevery stag mate with the nearest hind. nearest hind is found through figuring the distances for each stag and all hinds. The distance$dist$amid a stag in addition to all hinds in J-dimension space computation as follows:

$$dist_i = \left(\sum_{j\in J}\left(stag_j - hind_j^i\right)^2\right)^{1/2} \quad (12)$$

where$dist_i$denotes distance amid the i-th hind in addition stag. As a result, the minimum value in this matrix signifies hind selected. The action after hind selection is the mating process.

Selection the next generation: Next generation is formed by following two different strategies. At first, user retains all male RDs, all commanderbesides all stags, i.e. best solutionspercent out of all solutions. For the populationremainder in next generation, user selects hinds out of all hinds in this generation based on their fitness which is the objective functionthroughresidual energy with roulette wheel selection.

Stopping condition: The stopping condition possibly will bethe number of iteration, best solution quality ever found, or a time interval.

In general, RDA steps design has todeliberate the exploitation besides exploration phases satisfactorily. The phases tuning can be done by user with the used parameters in additionmathematical formulation. Therefore, the male RD roaring is the counterpart of local search in solution space for exploitation properties enhancement. Likewise, the fighting amid commanders in addition stags is also reflected as local search; nonetheless, in this process, only accept the better-observed solutions pertaining to optimal paths.The EARDA pseudo-code is revealed in Table 1.

Table 1. The pseudo code of EARD based routing

Initialize the IoV system model and Red Deers population$X$ as vehicle nodes.
Calculate the fitness$f(RE)$using eq.(5&6) and sort them and form the hinds (N_{hind}) and male RDs (N_{male}).
X*=the best solution of routing path.
While (t< maximum number of iteration)
For each male vehicle nodes (RDs).
A local search near his position.
Update the position if better than the prior ones.
End for
Sort the males and also form the stags and the commanders (Eq. 3& Eq. 4).
For each male commanders
Fight between male commanders and stags [16]
Update the position of male commanders and stags
End for
Form harems (7 to 9) for each male commanders (Eq. 10)
Mate male commander with the selected hinds of his harem randomly.
Select a harem randomly and name it k. (Eq. 11)
Mate male commander with some of the selected hinds of the harem.
end for
For each stags
Calculate the distance between the stag and all hinds and select the nearest hind (Eq. 12).
Mate stag with the selected hind.
End for
Select the next generation with roulette wheel selection.
Update the X* if there is better solution.
$t = t + 1$. //time interval
end while
return X* as the final optimal route

3.4.TSFNN with IWT for Traffic Intensity Calculation for calculating traffic intensity

In TSFNN, the first layer is the input layer, which is responsible for passing input variables to e second layer. The input value is the exact value besides number of nodes is the number of input variables. This layer devises three neuron nodes, also known as five variables, NV, DV, VMS, DOA,and VSF in addition to OU (optimal membership estimated through intelligent water drop algorithm (IWT)

In these section five parameters such as “number of vehicles currently moving on a road (NV)”, “Density of vehicle (DV)”, “vehicle movement speed (VMS)” and “Direction of arrival (DOA)” are greatly involved. The maximum number of vehicles (NV)computation is defined as (13)

$$\mathrm{Max}(\mathrm{NV_{ij}}) = \frac{\mathrm{RL_{ij}}}{\mathrm{L_v} + \Delta\mathrm{V}} \times \mathrm{NR_{ij}} \tag{13}$$

Where RL_{ij}notates road length, NR_{ij}signifies number of roads, $L_v$denotes vehicle average length in additionΔV is the average distance amid two vehicles. Likewise, definition of Density of vehicle (DV) is as follows:

$$DV_{ij} = \frac{NV_{ij}}{Max(NV_{ij})} \quad (14)$$

The road traffic condition can be attainedthrough vehicle movement speed (VMS analysis) as follows (7)

$$\upsilon_{vms} = \frac{\upsilon}{v_{max}} \quad (15)$$

where υ notates current average speed on the road and v_{max}denotes maximum allowable speed.

Vehicle speed and flow(VSF)**:**Additionally, the measured vehicle speed (V_{speed}) computation at certain time interval (t) is done through aggregating all section vehicle speeds contained by the alike time interval as follows:

$$V_{speed} = \frac{\sum_1^m V_p}{m} \quad (16)$$

where$m$represents number of trips covered by vehicle in the time interval (t) and (V_{speed})represents measured section travel speed for the same interval time (t). Then, the section travel speed $V_p$computation is done using equation: $V_p = \frac{L_p}{T_p}$. The flow rates were interpolated for obtaining values corresponding to the same time used for the vehicle speed.

Direction of arrival (DOA) offers direction from which the transmitted signal from RSU or cooperative vehicle reaches at the candidate vehicle receiver. The DOA estimation in angle errors presence can be stated as

$$DOA_{ij} = S_{DOA}(traffic) + AE_{DOA} \quad (17)$$

where, term AE_{DOA} denotes angle errors due to noises in DOA_{ij}. The term $S_{DOA}(traffic)$notates traffic signal DOA amid receiving vehicle besides cooperative vehicles.

Takagi-Sugeno-Kang Fuzzy Neural Network (TS-FNN):FNN possess the ability of processing the fuzzy information automatically due to the benefits of fuzzy logic system besides neural network. Various researchers has grabbed the attention due to very rapidt convergence speed as well as outstanding approximation performance. Two main methods in fuzzy system are involved in fuzzy system. One is fuzzy neural network based on Mamdha fuzzy rule, in addition other one is FNN based on T-S model. This research utilizes TS-FNN which is defined in the succeeding "if-then" rule form.

If x_1 is FS_1^i, x_2 is FS_2^i, $\cdots$, x_5 is FS_5^i:$here\ k = 5\ i.e.$, (NV, DV, VMS, DOA, VSF) (18)

$$y_i = FP_0^i + FP_1^i x_1 + \cdots + FP_5^i x_5$$

where FS_j^i represents fuzzy set, FP_j^i ($j = 1,2, \cdots, k$) is fuzzy parameters.

Fix input variable $x = [x_1, x_2, \cdots, x_k]$, each input variable x_j membership degree is computedon the basis of fuzzy rule:

$$\mu_{FS_j^i} = \exp\left(-\left(x_j - c_j^i\right)^2\right)\ j = 1,2, \ldots, n,\ i = 1,2, \ldots, n \quad (19)$$

In this formula, membership functioncenter is cij. k denotes number of the arguments. The number of fuzzy subsets is n. The fuzzy calculation method is utilizedfor membership degree estimation. The multiplication operator is utilized on the fuzzy operator:

$$\mathbb{w}_i = \mu_{FS_j^1}(x_1) * \mu_{FS_j^2}(x_2) * \cdots * \mu_{FS_j^2}(x_2),\ i = 1,2, \cdots, n \quad (20)$$

where "*" means multiplication.

The fuzzy model output value y_i might be attained from the fuzzy calculation:

$$y_i = \sum_{i=1}^{n} \frac{\mathbb{w}_i\left(FP_0^i + FP_1^i x_1 + \cdots + FP_5^i x_5\right)}{\mathbb{w}_i} \quad (21)$$

Conferring to the fuzzy rules discussed above, we TS-FNN is constructed [17].

IWD based optimization of Membership values for the Inputs: The membership values assigning is done for input optimization and thereby improving system accuracy as it influencesmeasuring traffic intensity efficiency . Thus, the process is termed as intelligent Water Drop technique [18] whose implementationinvolves four phases like initialization, Solution Construction, Reinforcement and termination. The membership value corresponds to each drop. The parameters significant fordrop efficiency are soil, velocity besides distance. There must be low soil content for anproficient water drop, velocity should be high as both are inversely proportional. The error function ought tobe low for membership function

This section describes phases involved in membership function optimization with the IWD. The graph has a major role in solution construction which acts as a distributed memory for the IWD algorithm. The IWD-CO flowchart is exposed in Figure 1. The subsequent subsections are devoted to the IWD components. A function $f(x)$ can be either minimized or maximizedwhich has M nodes $X = [x_1, x_2, \dots x_m]$as its input nodes. Here, N signifies the precision that is employed for segmentingpermitted range for every IoVnode.Presume that the search space range for node$i$ is amid numbers $\min i$ and $\max i$. Then, every consecutive N nodes in the IoVsignifies a binary string with N bits. Every IWD begins its journey from node1 and completes it by visiting last node. A selection mechanism for the IWD is desiredfornodes selection that is connected to the next nodes with EARD support. Next subsection articulates this membership function selection which is on the basis of edge selection mechanism.

Edge selection: Let an IWD is at node$i$besideschooses the IoV$X(k)$for visting the next node$i+1$. The probability $P_{IWD}\left(X_{i,i+1}(k)\right)$ for such a selection is defined by

$$P_{IWD}\left(X_{i,i+1}(k)\right) = \frac{f\left(soil\left(X_{i,i+1}(k)\right)\right)}{\sum_{l=0}^{1} f\left(soil\left(X_{i,i+1}(l)\right)\right)} \qquad (22)$$

Where $f\left(soil\left(X_{i,i+1}(k)\right)\right) = \frac{1}{0.0001+g\left(soil\left(X_{i,i+1}(k)\right)\right)}$ and (23)

$g\left(soil\left(X_{i,i+1}(k)\right)\right) = \begin{cases} soil\left(X_{i,i+1}(k)\right) & if\ c \geq 0 \\ soil\left(X_{i,i+1}(k)\right) - c & else \end{cases}$ where c is a parameter denotes $\min_{l=0,1} soil\left(X_{i,i+1}(l)\right)$

In the course of visiting nodes besides selecting nodes, the IWD updates soil carrying through itself in addition toeliminating some soil from the presently used node. The ensuing subsection articulates about this local soil updating.

Local soil updating: When IWD leaves node i by using node $X_{i,i+1}(k)$for attaining at node i +1, the IWD soil, $Soil_{IWD}$, and used soil node, $soil\left(X_{i,i+1}(k)\right)$, are upgraded as follows

$$soil\left(X_{i,j+1}(k)\right) = 1.1 * soil\left(X_{i,i+1}(k)\right) - 0.01 * \Delta soil\left(X_{i,i+1}(k)\right) \qquad (24)$$

$$Soil_{IWD} = Soil_{IWD} + \Delta soil\left(X_{i,i+1}(k)\right)$$

Here, the estimation of $\Delta soil\left(X_{i,i+1}(k)\right)$ can be,

$$\Delta soil\left(X_{i,i+1}(k)\right) = 0.001$$

Hence, the IWD has enabled to obtain high speed by the edge with less soil, when compared to the node with more soil. Once each IWD arriving at the final node of the graph of problem, local search algorithm application has progressed to the IWDs-driven solutions.

Mutation-based local search: During this process, IWDs-driven solutions are progressed through a mutation operation. In particular, node$X_{i,i+1}(k)$ is arbitrarily chosen from the solution edges that is swapped by further connecting node i to $i+1$ (if it could enhance the solution's fitness value). Then, the number of iteration is defined for this process (here defined 100 for each solution). In the current iteration, this mutation-based local search is carried out for each solution generated by IWDs. Post-process of this local search, the global soil is updated on the edges of the IWD algorithm'siteration-best solution.

Global soil updating: At the end of current iteration, iteration-best solution is identified from the solutions of each IWD, besides it is considered to be the solution with optimum quality (fitness) across each solution of IWD. Subsequently, the following equation updates the edges soil forming the solution IB_{sol}

$$soil\left(X_{i,i+1}(k)\right) = \min\left(\max\left(tempsoil\left(X_{i,i+1}(k)\right), \min soil\right), \max soil\right) \ \forall \left(X_{i,i+1}(k)\right) \in IB_{sol} \quad (25)$$

Where $tempsoil\left(X_{i,i+1}(k)\right) = 1.1 * soil\left(X_{i,i+1}(k)\right) - 0.01 * \frac{Soil_{IWD} * IB_{sol}}{(M \times N)} \forall \left(X_{i,i+1}(k)\right) \in IB_{sol}$ (26)

At this point, the interval $[\min soil, \max soil]$ is bounded with the global soil updating for preventing the underutilization of each edge. Consequently, the accurate estimation of the solutions IB_{sol} is not required for updating the global soil. The accomplishment of global soil updating indicates that a single iteration of the IWD is finished, then the further iteration initiates with new IWD. This progress will be continued till converged with maximum iteration count. Table. 2 depicts the algorithm for the selection of optimal membership value using IWD.

Table 2. Algorithm for optimal membership value Selection using IWD

Require: IWD Parameters and TSFNN input Ensure: Optimal Membership function OU 1. Initialize the input IoV 2. For each node Do IWD for getting best membership function, select the next node using Eq(22&23) 3. Update the visited node list and Update the soil of the IWD moving from node to node using Eq.(24) 4. Find the iteration best solution based on the objective function 5. Update the soil along the path selected through EARD based on the current iteration best solution by Eq.(25&26) 6. Update the global best solution based on the objective function as Error function

7. Increment the iteration count, and repeat the steps until the stopping criteria is met.
8. End for
9. For each node do TSFNN as in [17]
10. Display the filtered output image

Consequently, the effectiveness of the measuring traffic intensity has enhanced by giving the optimum membership to each node's input values. Due to this optimization, further enhancement will be added to the newly presented TSFNN in terms of traffic intensity measure. Figure 4.1 depicts the flow diagram of proposed TSFNN-IWD.

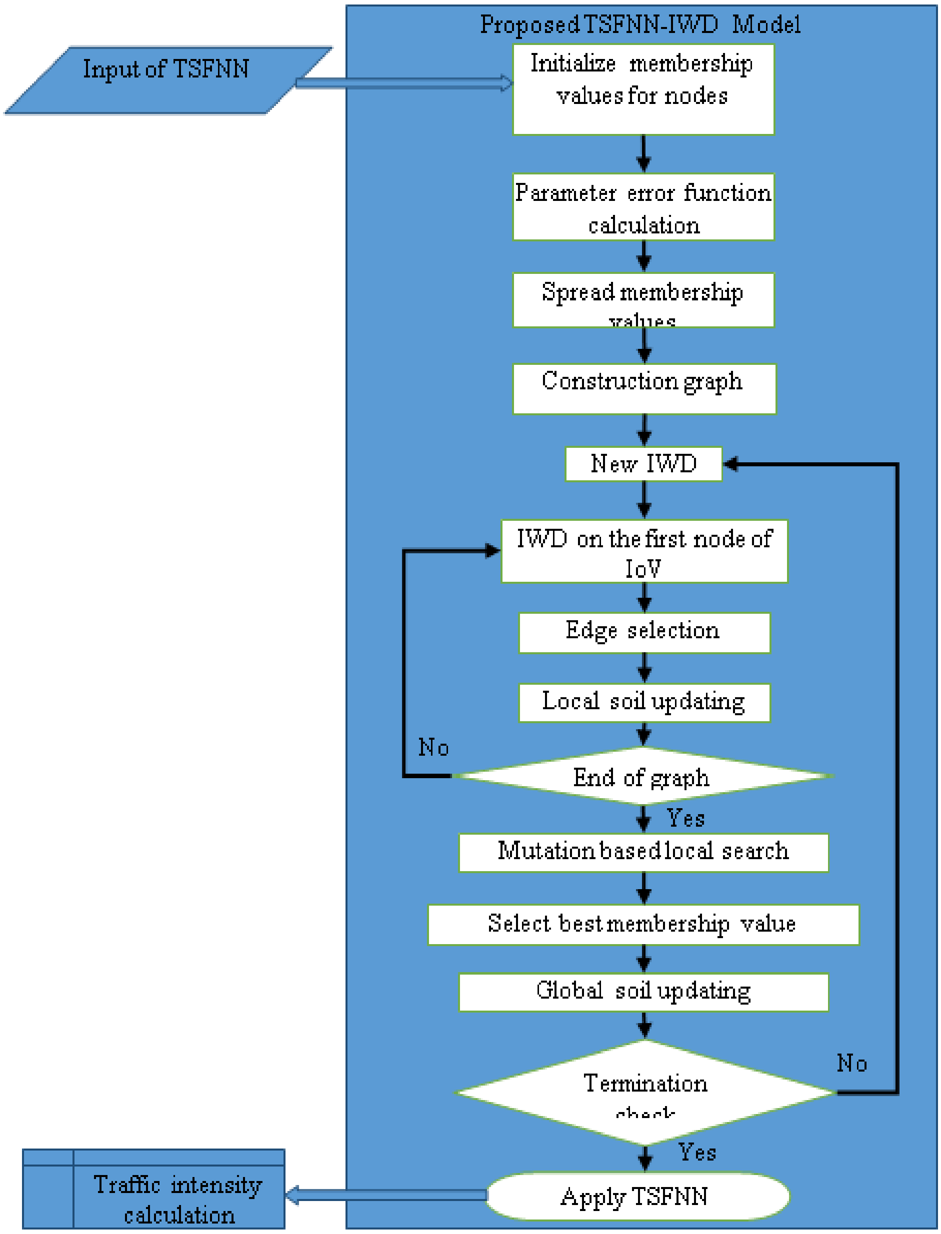

Fig.2.Traffic intensity measure suing TSFNN-IWT method

4. RESULTS AND DISCUSSION

In this segment, proposed IoV based route selection approach and the prevailing shortest path selection algorithms, like EACOFNNIoV, ELHACOGFNNGAIoV and EARD-TSFNN-IWD-IoV have compared by considering the parameters of ARTH, ARTT and latency. The empirical findings demonstrate the efficiency of the proposed EARD-TSFNN-IWD-IoVbased route selection method.

4.1.ARTH Comparison Results

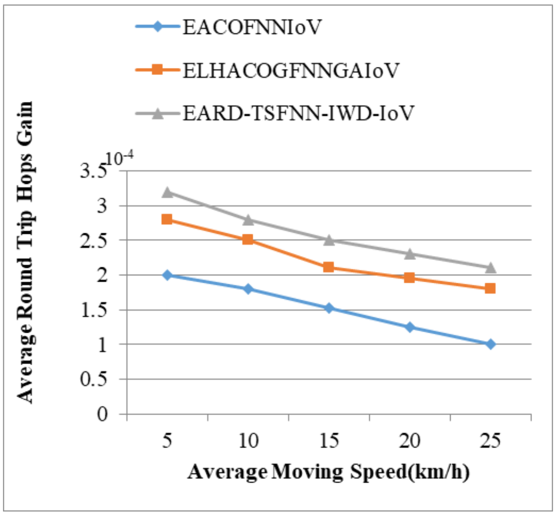

Fig.3. ARTH vs. Average Moving Speed (km/h)

Fig. 3 reveals the performance of proposed EARD-TSFNN-IWD-IoV and the existing EACOFNNIoV, ELHACOGFNNGAIoV on the basis of ARTH results. In the graph, the ARTH result increases concurrent to the nodes' average moving speed, which indicates the proficiency of the proposed EARD-TSFNN-IWD-IoV method to obtain the maximum ARTH rate that is superior to the EACOFNNIoV and ELHACOGFNNGAIoV models. Because, the proposed model is capable of identifying the optimal nodes in its neighbour using EARD, since it tends to attain optimum solutions by taking lesser processing time, deprived of being trapped into local minima.

4.2.ARTT Comparison Results

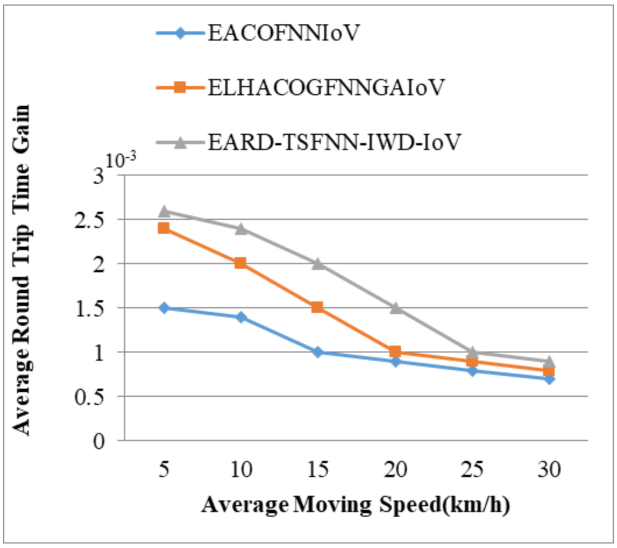

Fig.4.ARTT Vs Average Moving Speed (km/h)

In Fig. 4, the graph compares the performance of proposed EARD-TSFNN-IWD-IoV with the existing EACOFNNIoV, ELHACOGFNNGAIoV by considering ARTT results with its average moving speed. It represents the efficiency of the proposed EARD-TSFNN-IWD-IoV method to acquire the higher ARTT value that is superior to the EACOFNNIoV and ELHACOGFNNGAIoV models. During the process, ARTT decreases at the time of average moving speed rises in the network. Because, the proposed model has the capacity to enhance the route discovery by processing the optimal path selection when compared to the conventional frameworks, since the EARD lessens the time for implementation, besides optimizes the membership values through IWT, which augments the traffic intensity measure.

4.3.Latency Comparison Results

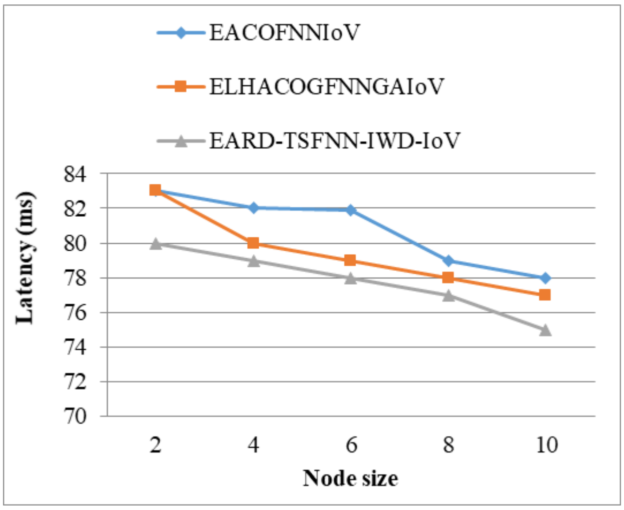

Fig.5. Latency Comparison Vs Cache size

Fig. 5 demonstrates the performance comparison of proposed EARD-TSFNN-IWD-IoV and the conventional EACOFNNIoV, ELHACOGFNNGAIoV on the basis of Latency results at various sizes of node. It can be observed from the graph that the increasing node size gradually reduces the rate of latency, which signifies the proficiency of the proposed EARD-TSFNN-IWD-IoV method to surpass the traditional strategies by 4% to 18% for extensive range of node sizes. Due to the proper cache utilization, the optimized routing methodology provides the better performance, as the IWT procures optimal solutions in TSFNN. Besides, the GA has further involved for the optimization of the centres of each membership function, and the enhancement of traffic intensity measure that lowers the latency values.

4.4.Throughput

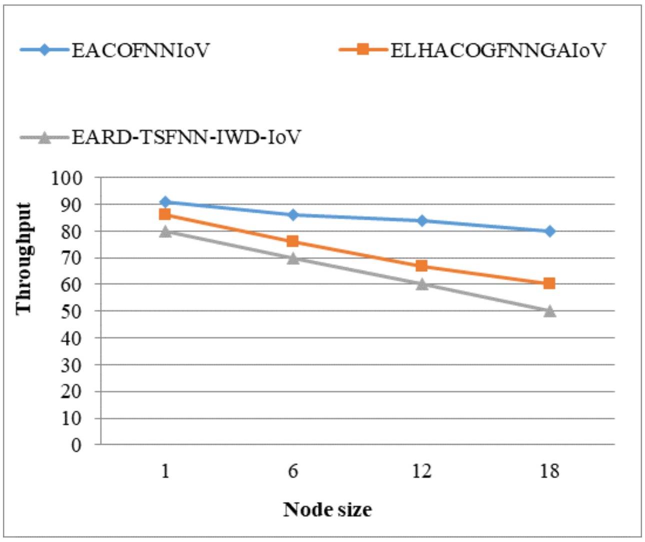

Fig.6. Throughput Comparison Results

Fig. 6 compares the performance of proposed EARD-TSFNN-IWD-IoV and the existing EACOFNNIoV, ELHACOGFNNGAIoV methods in terms of throughput, in which the proposed EARD-TSFNN-IWD-IoV method proves to be efficient than the traditional methods. Besides, it is evident that the additionally increased nodes also obtaining the higher throughput rates. Even though it is able to provide the same planned path in normal traffic situation, outcomes reveal that the EARD-TSFNN-IWD-IoV proves its betterment compared to other algorithms, since the EARD has the ability to effectively modify the planning path in accordance with the dynamic traffic situation, besides indicate an optimal path with integrating traffic intensity. Hence, it could furnish the efficient solution for environmental pollution and energy consumption during the highly complicated urban traffic environment.

5. CONCLUSION AND FUTURE WORK

Ultimately, an innovative routing methodology has proposed on the basis of EARD-TSFNN-IWD-IoV in two different stages, in terms of attaining the scalable in addition to stable topology in IoV networks. For maintaining IoV network connectivity, the presented algorithm utilizes the proposed EARD-TSFNN-IWD-IoV algorithm in accordance with traffic intensity. During this research, the core objectives, such as the avoidance of local optimum problems and network dissemination problems have successfully achieved pertaining to develop the innovative concepts. Besides, the better performance of the proposed algorithm has manifestly established, concerning the construction of effective and qualitative V2I communications, and ensuring consistent information delivery to each vehicle. Moreover, the cost of traffic congestion can considerably be reduced through EARD-TSFNN-IWD-IoV approach, besides it is able to furnish the inspiration to resolve the present traffic congestion. In addition, the proposed algorithm chooses a highly efficient and appropriate planning path, according to various traffic information and planning necessities. Through the simulation outcomes, it can be observed that the introduced algorithm has the ability to attain the appropriate path in the real-time vehicular traffic networks based on the various requirement (i.e. the shortest path planning and the shortest time planning).

The authors tend to extend this research work further by focusing on the enhancement of system flexibility through upgrading the segmented structure to a hybrid structure with vehicle-to-vehicle communications-based traffic-flow estimation. Also, the enhancement of the local segment traffic congestion prediction and origin-destination traffic congestion service can be focused in order to take part in the hybrid segmented structure.

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