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Comparing Artificial Bees Colony Algorithm and Firefly Algorithm to Achieve Optimization in Route Selection Processing Time in VANETs

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***Abstract*-In achieving Intelligent Transportation System (ITS), a new trending area in networking is Vehicular Ad-hoc Networks (VANETs). It is a sub branch of Mobile Ad-hoc Networks (MANETs) where all the nodes or devices are interlinked and interconnected wirelessly. The challenges that a VANET faces while communicating within a network are signal fading, routing decision making and connectivity hitch. All these three mentioned problems have already been discussed and well researched in history by using conventional techniques as well as intelligent techniques based on artificial intelligence. Amongst all these three issues we are focusing on mitigating decision-making problem for optimal route selection. In order to solve this issue, researchers have found that meta-heuristic intelligent algorithms such as, Artificial Bees Colony (ABC) and Firefly Algorithm (FFA) are more efficient algorithms as compared to traditional approach. In this paper we compared ABC and FFA to check which algorithm runs faster in order to achieve routing decision in lesser time**

***Index Terms*-- Artificial Bees Colony algorithm, Firefly algorithm, Intelligent Transportation System, Meta-heuristics, Mobile ad hoc network (MANET), Vehicular ad hoc networks (VANETs).**

I. INTRODUCTION

MANET has piqued the interest of researchers over the last decade due to its potential uses in a variety of fields where infrastructure installation is impractical. MANET is a self-organizing network that connects with each other via wireless networks [1]. VANET is a subset of MANET that shares many of its properties. VANET is a subset of MANET that shares many of its properties. A VANET is a group of self-configuring networks. Road Side Unit (RSU) equipped automobiles and On-Board Unit (OBU) are the network's nodes. The purpose of VANETS is, to highlight the most critical components of MANETs to make ITS applications easier to implement [2].

VANET plays a key role in the development of ITS [3]. Vehicles are now designed to not only communicate with one another, but also to receive data from and deliver data to infrastructure components. They have little or no previous framework in these immediately shaped systems because the hubs can send, get, and forward information among themselves, communicated with the parts total to the system foundation units situated alongside the road's RSUs, or the Vehicle-to-Infrastructure (V2I) forming a VANET. Figure 1 shows a standard VANET architecture. Since VANETs are becoming an essential component of communication, it is necessary to have efficient routing among the vehicles.

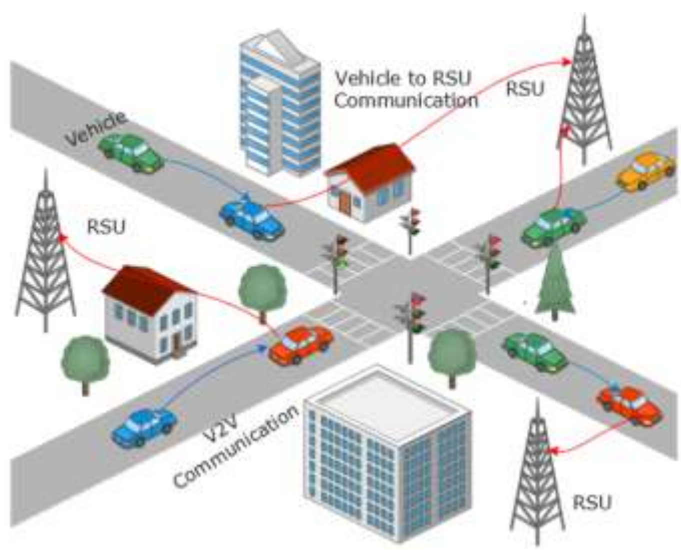

FIGURE 1: Standard VANET Architecture

In VANETs, routing techniques and protocols are the most researched area [4]. The routing protocols in network layer, decides the performance of VANETs [5]. It provides efficient and effective data communication. Efficient routing in VANETs eliminates extra use of bandwidth, ensures efficient communication and makes the flow of data smooth. The three primary goals of efficient routing are, to update the new route at runtime if a better one becomes available, to determine the most efficient route from source to destination, (handover), and to preserve the route in the event of route failure [6]. The precondition for forwarding any data between two nodes is to find the most suitable path between sender and receiver. Increased mobility in VANETs puts conventional routing algorithms to the test. The traditional problem-solving algorithms performed poorly in MANET. Thus, the need for more advanced and robust algorithms surfaced.

The process of achieving the most appropriate solution for a given objective or purposes by imposing certain constraints is known as optimization [7]. In the pursuit of finding the solution to the optimization problems for VANETs, we study two distinct optimization strategies to identify the shortest path for the mobile node during runtime, based on the limitations of existing systems. Algorithms for optimization are categorized into two categories: deterministic and stochastic algorithm [8]. With some randomness, Heuristic and meta-heuristic algorithms are stochastic approaches, which implies they pursue multiple paths to get the best result. Heuristic algorithms are issue-specific strategies for addressing any problem, but metaheuristics are a more advanced sort of heuristic methodology that primarily employs randomization and local search [9].

The metaheuristic technique includes algorithms such as ABC, FFA and many others. The ABC algorithm is a global optimization problem-solving swarm intelligent algorithm. It is experimentally proven to be a reliable, efficient, and successful optimization strategy [10]. The mechanism of ABC is divided into three groups: employed honey bees, observer honey bees, and scout honey bees. Hired bees make up half of the ABC algorithm, while the observers make up the other half. Each food source represents a worker bee who reaps the advantages of his or her own food source and returns to the hive to tell the other bees about it. Each observer bee watches the employed bees' dances and attempts to locate a food source [11]. Inspired by the flashing behavior of fireflies in nature, Yang invented Firefly algorithm which, is an evolutionary optimization algorithm optimization algorithm [12]. FFA is a recently developed nature-inspired method for solving nonlinear optimization problems. The strategy is based on the behavior of glowworms (fireflies). Fireflies have a proclivity to attract one another and establish groups based on certain criteria. In this algorithm, fireflies use flash system to attract other flies [13].

Arrangement of this paper is as, section I discusses Introduction, section II covers background and the related work, in sec III swarm intelligence technique in meta-heuristic algorithms is discussed. Sec IV shows results and experiments and conclusion and future work is being discussed in sec V.

II. RELATED WORK

Swarm Intelligence (SI) is a set of meta-heuristics optimization strategies inspired by nature [14]. Various algorithms such as ABC [15] and FFA [16] are implemented by the researchers, to increase the optimization in VANETs. In [9] authors utilized bio inspired algorithms such as, ABC and FFA to optimize routing in VANETs. In [17], the authors presented CBQoS-Vanet, a new QoS-based routing system for VANET that uses the ABC algorithm to improve communication.

The authors of [18] presented a dynamic connectivity scheme for VANET using the ABC algorithm. [19] presents enhanced and integrated Artificial Bee Colony, oriented Multicast Routing (EIAC-ABCMR), a multicast tree determination issue that enforces multi-constrained QoS fulfilment by minimizing cost, latency, and jitter with better bandwidth for improving data transmission efficacy. An optimization framework (FA-OLSR) based on Firefly is presented in [20]. The framework comprises of three phases i.e.(i) The optimization Phase(ii) A Network Simulation phase and (iii) A traffic generation phase. In [21], a reputation-based weighted clustering protocol (RBWCP) for VANET is proposed. The proposed RBWCP utilizes firefly algorithm to streamline the boundaries of RBWCP in VANETs. Authors in [22], evaluated performance of different routing protocols. In experiment, various parameters were studied and shortest paths were found more conveniently by ABC algorithm

III. SWARM INTELLIGENCE IN META-HEURISTICS FOR VANETs

Over the past decade the idea of biological bee communications has trends to penetrate the domain of vehicular networks. VANET primary reason was for driving passengers' comfort and safety on the road. In VANETS, the transmission of real-time safety messages is crucial and time-sensitive due to the nature of Inter-Vehicle Communication (IVC). Real-time messages from source to destination must be conveyed in a timely manner with reduced delay bound. Messages or data packets that arrive at their destination after the designated time limit are deleted, resulting in packet losses. The patterns of bee communication and information transfer among bees during foraging have piqued the interest of the VANET research community. At VANET, improving the packet delivery ratio and optimizing data packet transfer in various applications is a difficult task. To provide QoS, an optimization technique inspired by the intelligent foraging behavior of honeybee swarms could be used to provide connection stability, which provides cluster-based routing and applies Artificial Bee Colony and Fire Fly optimization techniques to successfully optimize route discovery in VANET. The introduction of artificial intelligence in bees has made it possible, as it works on the basis of collective intelligence. Nature inspired algorithms and bio-inspired algorithms, for example, can be classed as single-agent population-based algorithms or multi-agent population-based algorithms [23].

ARTIFICIAL BEE COLONY ALGORITHM (ABC): When a bee finds a food source in ABC, it alerts the other bees by dancing in its own special way. This signals the other bees to the food source's position, directing them in the right direction. The presence of these bees attracts a significant number of hungry bees to the region. The three categories of bees in ABC are employed bees, spectator bees, and scout bees. Employed bees do a local search and inspect adjacent food supply locations depending on factors such as nectar flavor, quantity, and closeness to the hive. The bees then use the dance floor to share this vital information with the other bees in the hive. The flowchart of ABC algorithm is shown in Fig 2.

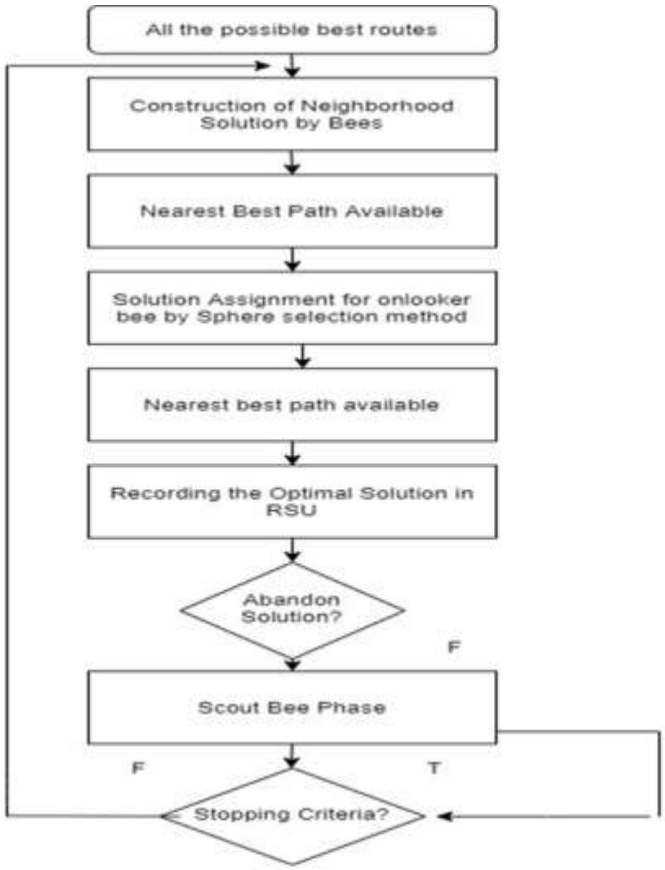

FIGURE 2: Flowchart of Artificial Bee Colony Algorithm

It's tough to converse with a car that has travelled a long distance. The key aspect that causes the signal to fade is the distance between the cars. When a signal or communication must travel a long distance, it is possible that it will be lost due to the distance. As a result, we'd use the Artificial Bee Colony algorithm in the routing process to prevent signal fading as much as possible. Every vehicle passing through a Road Side Unit is recorded in the Road Side Unit. As a result, we gather the traffic count when the car returns to the Road Side Unit, which is determined based on the number of Road Side Units the vehicle has gone through. As a result, a message will be sent along the path with the lowest average vehicle density. This would ensure that the network's stability remained constant throughout time. The same strategy employed by bees to discover the next food source is being applied to solve the signal fading problem. When the food supply is out, the observer bee is dispatched to find the next food source. Consider a car that is now travelling down a path with two paths. The average traffic density of the RSUs in both pathways is compared, the message is sent down the path with least amount of traffic congestion. As a result, message is passed to the vehicle travelling on less congested path. Because practically comparable vehicles are driving on the road at more or less equal distances, the network is made stable by eliminating signal fading concerns. The signal fading problem can be overcome by directing the vehicles to drive in a path with a lower traffic density. This would make the VANET more effective because the messages would be sent as planned without the signal fading issue. When this idea is executed, the dynamic network that is produced will be more stable.

FIRELFY ALGORITHM: A meta-heuristic method, Firefly algorithm (FFA), is typically used to solve production and scheduling issues [16].The following are three FFA concepts:

- Fireflies: thought to be of the same sex, and all fireflies, regardless of sex, are attracted to each other.
- The brightness of the fireflies attracts them: a low-brightness firefly will migrate towards a high-brightness firefly. The brightness and distance are proportionate.
- The objective function determines the brightness of a firefly. The motivation for the algorithm is the self-organized behavior of Fireflies.

In FFA, each vehicle (node) behaves as a firefly. When the intensity frequency or value of the flashes is high, the probability of selection is higher during communication. The intensity value is determined by the value of the goal function. Fig 3, depicts the flow chart for FFA.

When we want to locate a path from a source node to a destination node, we may use this approach to determine the shortest path between them. The objective function value is used to create a sorted list, with rows indicating the source vehicle and columns reflecting the number of vehicles in that region. At the source vehicle, At the source vehicle, a controlled flooding mechanism is used, and packets are transmitted to other automobiles in the region using this manner. Following that, the vehicle with the highest objective function value (depending on density and speed) will be chosen.

Then we figure out if the intermediate node is a destination node or not. If this is not the case, repeat the method to locate the destination node. If this is the case, use the reverse path to get back to the source vehicle. The new objective function's value will be determined by the density. It is possible to predict next position of the vehicles and make better route decisions with the help of prediction.

IV. EXPERIMENTAL SETUP AND RESULTS

To observe the behavior of both the intelligent algorithms ABC and FFA, we ran the results on MATLAB 2019Ra. The optimization algorithms used in this study used the following parameters for evaluating the experiment.

In past research has been done on optimizing the routing path selection problem i.e. choosing the best available path. But here, we wanted to observe the decision making process time for routing and behavior of VANET, we only focused on increasing and decreasing number of vehicles in our experimental setup. In order to obtain our desired simulation within a network and fixed area when a vehicle moves and tries to communicate with neighbor devices and vehicles, how much time it takes to record the information of network on RSU. Simulation results of artificial bee colony algorithm (ABC) are shown in Fig. 4, Fig. 5, Fig. 6, and Fig. 7. Simulation results of firefly algorithm are shown in Fig. 8, Fig. 9, Fig. 10, and Fig. 11.

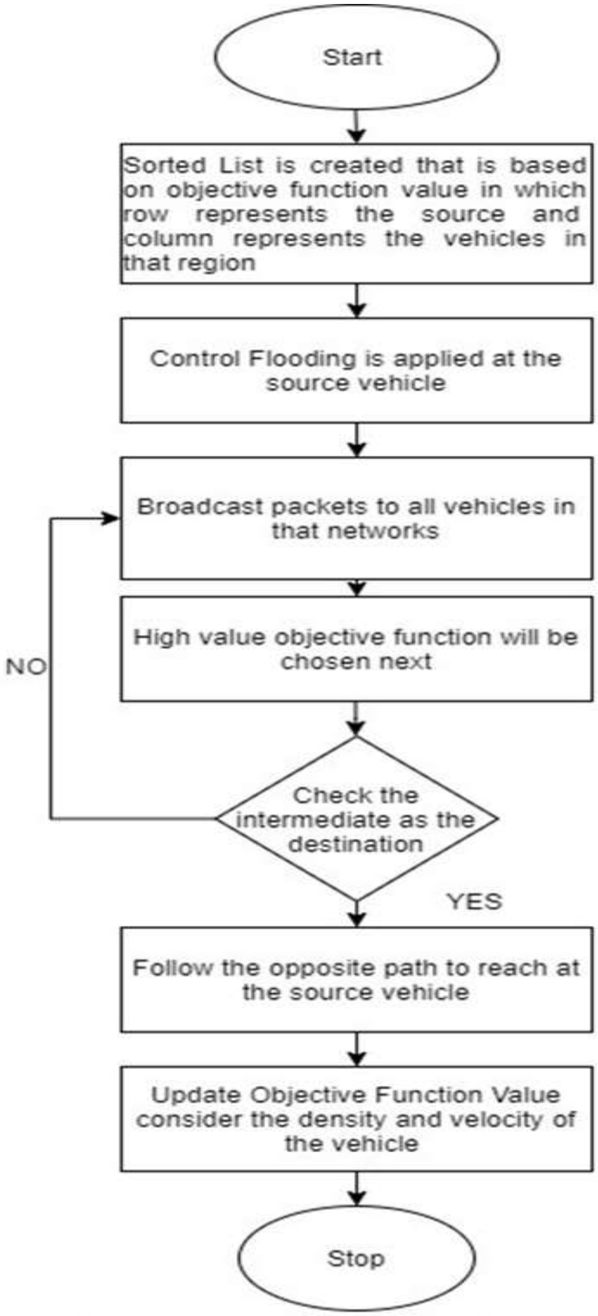

FIGURE 3: Flowchart of FIREFLY Algorithm

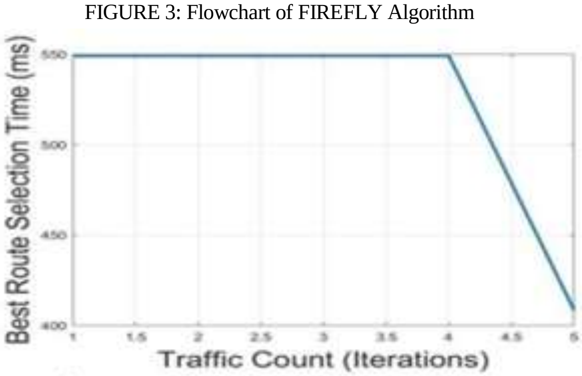

Fig 4. No of vehicles = 150,Iterations = 5

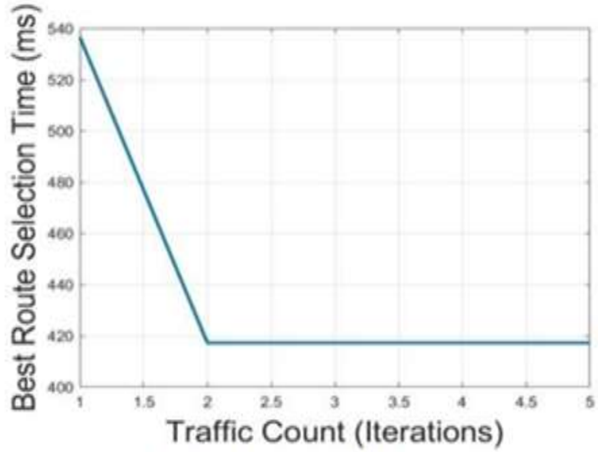

Fig 5. No of vehicles = 150, Iterations = 10

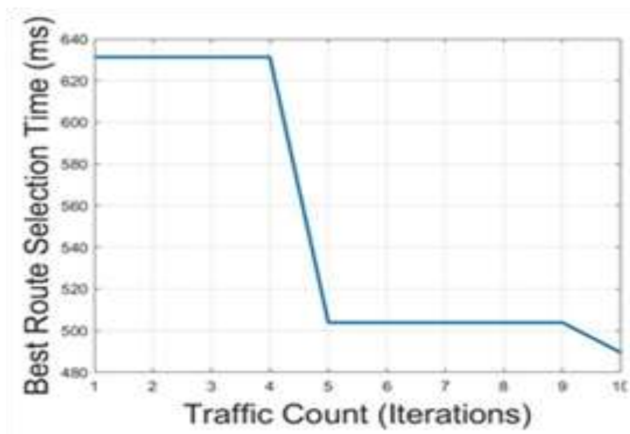

Fig 6. No of vehicles = 250, Iterations = 5

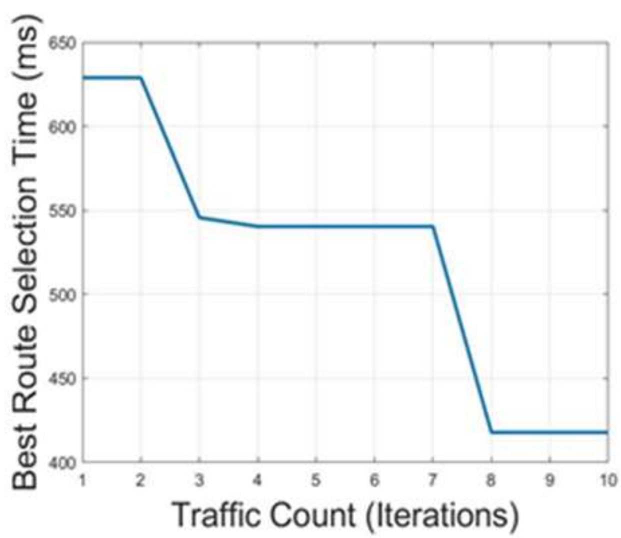

Fig 7. No of vehicles = 250, Iterations = 10

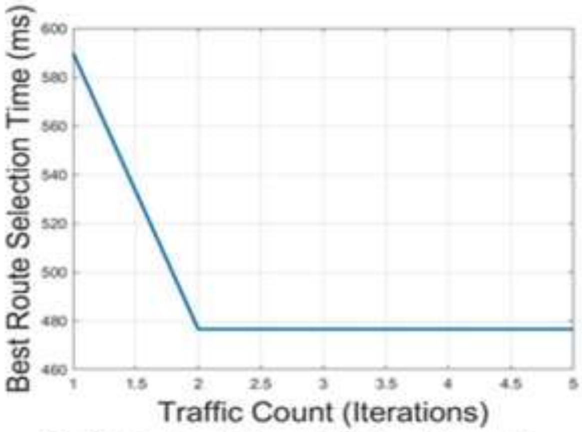

Fig 8. No of vehicles = 150, Iterations = 5

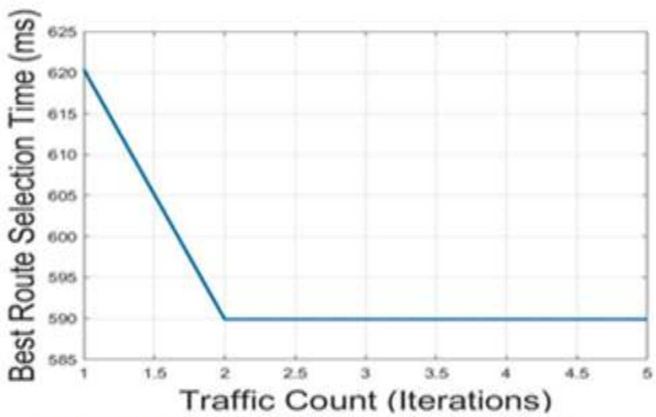

Fig 9. No of vehicles = 150, Iterations = 10

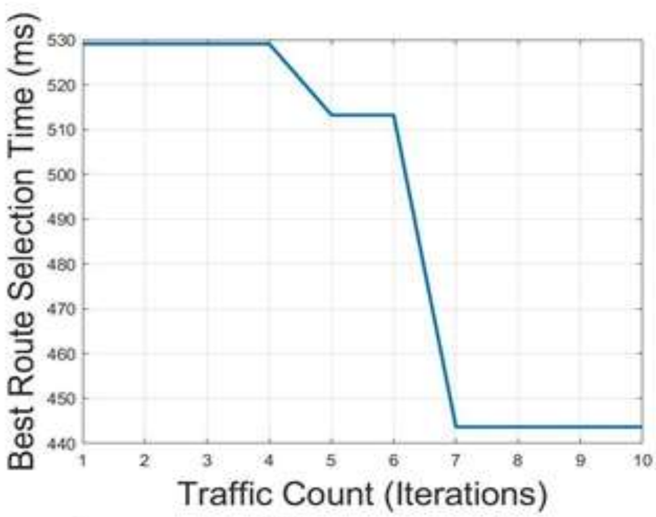

Fig 10. No of vehicles = 250, Iterations = 5

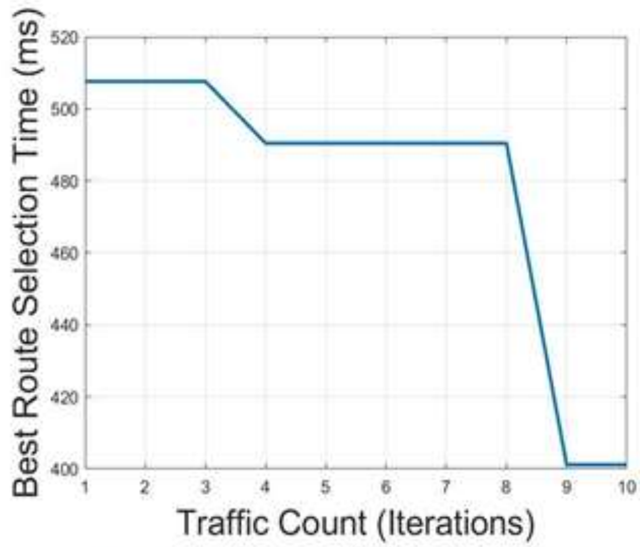

Fig 11. No of vehicles = 250, Iterations = 10

The graphs here are showing observations at 30 RSUs. As discussed above in sub section A of section 3, here one iteration means storing record of the whole network once. In further iterations it will keep on updating the stored record on RSUs that will eventually minimize the storing and retrieving time of information for routing and will result in quick decision making.

V. CONCLUSION AND FUTURE WORK

For making decision to select best route in a highly dense VANET, when applying ABC on setting minimum number of vehicles to 150 with 5 iterations as shown in Fig 4 and Fig 5. It takes 194 ms to process and with 10 iterations, it takes 106 ms average. When we set vehicles to 250 with 5 iterations in Fig 6 and Fig 7, it takes around 224 ms and with 10 iterations 93 ms on average.

When applying FFA on setting minimum vehicles to 150 and 5 iterations in Fig 8 and Fig 9, it takes 24,0000 ms and with 10 iterations, it takes average 10,0000 ms. On 250 vehicles and 5 iterations shown in Fig 10 and Fig 11, it takes 20,8000 ms and with 10 iterations 11,0000 ms on average.

After performing the iterations and running the algorithms on vehicles, we have successfully achieved the results that, ABC is much faster than FFA. We are not taking into account the accuracy of result here. Moreover, it can be seen on maximum number of vehicles and maximum number of iterations ABC is performing better, shown in the figures above. FFA is proved to be slower than ABC in this situation but in actual it provides results far more rapid than conventional and heuristic algorithms For future this work could be continued by converting these simulations into big data and applying data mining and data science techniques to refine it and furthermore implementing Machine Learning for predicting and making VANET proactive and self-organized.

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