The proposed novel approach of this paper utilizes two meta-heuristic based approaches namely firefly and water drop algorithm for optimizing Quality of Service (QOS) parameters in MANET-IOT based networks. Firefly Algorithm will provide accretion of routing by making routing less-complex, and more QOS efficient. Such blend of firefly calculation correlated with water drop algorithm in IOT and MANET directing standards can design the endurance of sensors in general versatile IOT framework. There is significance in choosing what number of bunch heads is required and which sensor hub becomes group head.
MANET organize hubs are designated as a group head and a proactive steering convention is utilized so that it becomes conceivable to deal with the circumstances of the data table of the system and refreshes the same. Hubs that lose their QOS quickly are perceived and constrained for exchanges. NS 2.34 simulator has been utilized in order to carry out all the examination of a steering way over the MANET-IOT structure. Proposed methodology deals with optimization of conventional routing methodology through firefly algorithm correlation with water drop algorithm with MANET directing standards by expanding the endurance of sensors in the general internet of things framework.
The primary aftermath of this work is QOS utilization in the worldwide MANET-IOT structure and to deal with it an arrangement of direction enhancement, which can help in availability and arrangement of administrations over worldwide future internet foundation serving health, pharmaceutical and agriculture industries for significant purposes.
The upcoming sections of this paper will focus upon the structure buildings of ingenious firefly algorithm and water drop algorithm in Section 2 through their related work. Section 3 will display simulation results of ingenious firefly algorithm correlated with water drop algorithm. Section 4 will provide in firm discussions and conclusion with future work and applications of proposed model described in Section 5 followed by References.

2. Related Work

This section of related work highlights upon literature review conducted for this research analysis focusing on the various features of bio-inspired algorithms followed by methodology of firefly and water drop algorithms.

2.1 Bio-inspired Meta-heuristic Algorithms

Various optimization algorithms when applied through different mathematical based capacities referred as the numerical target capacities may or may not be subjectively relative on its profound factors. Due to huge reliability produced by various numerical calculations of the streamlining techniques, they are progressively and recursively adopted in various areas of science and other related fields. Deterministic and stochastic are the two methodologies that provide differentiation of the optimization approaches which may lead to the achievement of goal or reaching very close-by the target. The optimization algorithms take into account similar types of arrangements when calculation starts with a similar type of beginning scenarios.
The stochastic based optimization approaches are described based on a haphazard value called the stochastic segments in an algorithm. Since stochastic approaches infer similar starting conditions the outcomes produced by them do not create equivalent and ideal results for various related problems. This leads to scope of conceivable outcomes for framing of the stochastic part. The strategies thus produced are referred as meta-heuristic approaches that make straightforward random routes by testing the pursuit space or make arbitrary strolls.
Firefly algorithm is a meta-heuristic calculative scenario that is stochastic in nature and was created by Yang [9, 10, 11]. FRA is a nature propelled on-going advancement calculation roused through firefly's social conduct. The algorithm is dependent on the blazing and fascination attributes of the fireflies. FRA is a bio-propelled algorithm belonging to the family of Genetic Algorithms (GA), the Particle Swarm Optimization (PSO), the Ant Colony Optimization (ACO) and the Artificial Fish Swarm (AFS) algorithm which have roused wonders in optimization of various real world scenarios [12, 13, 14].
All the bio-inspired algorithms mentioned above follow practices of nature and that of creature world. The bio-propelled calculations mostly are dependent on the conduct and development of herds of flying creatures. ACO relates to social conduct of ants and their correspondence of location of an ideal way through their state and capacity supply. PSO relates to development of groups of various winged animals following the pattern of the investigation of common aggregate conduct. Firefly is also a bio-inspired algorithm that is motivated along aggregate behavior of flame-flies explicitly by the way they draw in one another. Past examinations have shown that the FRA acquired great outcomes, demonstrating its

predominance over some bio-motivated strategies [15, 16, 17, 18, 19, 20]

2.2 Ingenious Firefly Algorithm

This research paper focuses in applying the FRA for optimizing the routing approach of traditional zone routing protocol of MANET leading to accretion of QOS parameters which when applied to real world IOT based platform will reduce the various hiccups of data transfers in various engineering, emergency, pharmaceutical, health and agriculture backgrounds [21, 22]. FRA utilizes the action of ingenious fireflies to solve the global accretion bound constraints. Various mathematical calculations required by the firefly algorithm to address the problem of optimization are discussed below:

:

$$f(x) \qquad \text{-------}\ (1)$$

$\in p \leq x \leq q$

Where:

; f(x) is referred as a continuous nonlinear objective function

; p is the lower bound of the variables

; q is the upper bounds of the variables.

The ingenious FRA is based on three main principles stated below [23]:

a) Fireflies are unisex that implies that the population of fireflies attract one-another.
b) There is a direct and proportional relationship between attractiveness and brightness of the fireflies. A firefly that is less bright always moves towards a brighter one. If a firefly doesn't find a brighter firefly it moves randomly. As stated before attractiveness of fireflies is directly proportional to their brightness; so this attractiveness decreases with the increased distance between the fireflies.
c) The brightness also referred as the light intensity of the fireflies is closely related to the optimization function. Hence firefly's brightness becomes directly proportional to the objective function's value [24, 25].

The above 3 principles are applied on the traditional routing algorithm in the proposed approach to optimize its QOS parameters performance. As stated above FRA is based on the 2 basic fundamentals of intensity of light emitted and the attractiveness degree that is being generated along the two basic fireflies. The intensity of light of firefly i, Ii is dependent on the light intensity Io of the other firefly j and the distance between fireflies I and j respectively. There is a monotonic and exponential variation between Ii light intensity and distance rij which is given as

$$Ii = I0e\text{-}\gamma rij \qquad \text{------------}\ (2)$$

Where:

; γ is the coefficient of light absorption.

Generally, $\gamma \in [0: +\infty]$,taken as 1in practice.

Firefly's i's attractiveness βij depends on intensity of light that is seen by adjacent j firefly and its rij distance. Hence βij attractiveness is calculated as:

$$\beta ij = \beta 0e \qquad \text{------------}\ (3)$$

Where:

; βij is referred as the attractiveness with distance rij=0.

Fireflies i and j with distance rij specified at xi and xj is calculated through the Cartesian distance as:

$$rij = \| xi\text{-}xj \| \qquad \text{-----------}(4)$$

The calculative development of one firefly towards another most brilliant firefly is specified as:

$$xi + \beta ij(xj\text{-}xi) + \alpha \varepsilon ij \qquad \text{-----------}(5)$$

Where:

;εij is an referred as an irregular parameter of uniform dispersion of scale

The light intensity of a firefly is dictated through target work esteem.

The pseudo code of the Firefly Algorithm for bound obliged streamlining issues can be condensed as pursues:

1. Population of h fireflies is initialized as xi = 1, 2…..h.
2. Light intensity f(xi) is being computed, for all population of fireflies, i = 1, 2…..h.
3. While (stopping criteria doesn't meet) do;
4. for i=1to h
5. for j=1to h
6. if f (xi) > f (xj) then
7. Move the firefly i towards firefly j using (3)
8. end if;
9. end for;
10. end for;
11. Update the intensity of light f(xi) for all the fireflies.
12. Rank all the fireflies and find the current best firefly
13. end while;

2.3 Intelligent Water Drop Algorithm

The Intelligent water drop routing algorithm (IWDRA) [26] is a swarm-based nature-propelled enhancement calculation which executes the common conduct of water drops and their activities and responses when they stream inside waterway's bed. In nature, water drops in streams discover their approaches to oceans and seas in spite of all obstructions in their ways.

The earth's gravitational force powers the water drops from stream to the goal. Since water drops face various types of snags in their way so they don't stroll in straight way and their ways appear to contain different turns and curves. At the point when the water drop moves starting with one point then onto the next point in front, it conveys a measure of soil and as it ends up close to the goal the measure of conveyed soil increments while the dirt in the stream's bed diminishes.
The water drop has additional speed and its speed assumes a significant job in deciding the measure of the dirt which will be expelled from the waterway's bed and conveyed by the water drop. The drop of water that possesses higher speed will assemble large amount of soil from its way. The acceleration of the drop of water relies upon the way to such an extent that as the water drop streams over a way with little soil its speed expands more than when it streams over a way with impressive measure of soil [27, 28, 29].
The water drops favor the simpler way when they need to pick between a few ways from source to goal. The IWDRA calculation is a populace based calculation in which a lot of Intelligent Water Drops (IWDs) are put randomly on the hubs of the diagram and after that each IWD heads out starting with one hub then onto the next until it reaches the target. While each IWD moves starting with one hub onto the next measures the dirt of the edges interfacing, the visited hubs are altered. As time slips by the edges of better arrangement will contain less soil. After all IWDs build their path the all-out best arrangement will be chosen and then a similar procedure will be rehashed at various occasions [30, 31, 32]. The accompanying calculation condenses the fundamental strides of IWDRA calculation.

The pseudo code of the IWDRA is given below:

• Input: Problem informational collection (formulated as completely associated chart).
• Output: An ideal arrangement.
• Main advances:

1. Introduce the static parameters which remain constants amid the pursuit procedure.
2. Introduce the dynamic parameters (i.e., parameters which are changed after every emphasis).
3. Spread IWDs having an IWD number haphazardly on the built chart.
4. Update the rundown of visited hubs of each IWD, to incorporate the hub just visited.
5. Rehash the accompanying strides for each IWD, where:
   ;k∈ [1, iwd number] with halfway arrangement and:
   (a) i = the present hub for drop k.
   (b) j = next hub,
   (c) Move drop k from hub i to hub j.
   (d) Update the accompanying parameters.
   – Velocity of the drop k.
   – Soil incentive inside the drop k.
   – Soil incentive inside the edge eij.
   (e) End for
6. Apply a disentangling procedure utilizing expansiveness first hunt to uncover the network structure for all arrangements developed by IWDs.
7. Select the Emphasis Best Arrangement (EBA) from all arrangements.
8. Update the dirt estimations of all edges incorporated into the Cycle Best Arrangement (CBA).
9. Update the Absolute Best Arrangement (ABA). On the off chance that (quality (ABA) ⩽ quality (EBA)) then: ABA = EBA.
10. Increment iteration count by one.
11. Check the stop standard.
    – While (the most extreme number of cycles hasn't arrived)
    Do
    – Repeat stage 2 to stage 10
12. Return the complete best-arrangement (CBA)

Upcoming section of this paper will validate the proposed approach through simulation results.

3. Simulation Results

The proposed "Remit Accretion in IOT Networks Encircling Ingenious Firefly Algorithm Correlating Water Drop Algorithm" is validated through NS 2.34 simulator by taking into considerations the following simulation parameters; Network Area (NA) = 1000x1000 m2, Velocity of nodes= 0~20m/s, Size of packet= 512 bytes, Type of Traffic= Constant Bit Rate (CBR), Connections =20 and Rate of Packet= 4 P/s. The results depicted in Fig.2-Fig.6 utilizes the traditional hybrid routing protocol MANET namely ZRP (Zone Routing Protocol). Since the routing results of ZRP are not optimized for utilization in real time IOT-MANET so the proposed and simulated approach of this research analysis presents QOS solution improvement and optimization through the ingenious firefly routing algorithm and intelligent water drop routing algorithm.

But when both the approaches were compared against one another the ingenious firefly routing algorithm produced better and optimized results as compared with IWDRA.

3.1 End to End Delay (E2D) Calculation of FRA Correlated with IWDRA

Simulation time is taken as the comparison parameter for the calculation of end to end delay of the proposed FRA correlated with IWDRA. End to end delay is the overall delay suffered by the data packets to move across the source and destination in an IOT-MANET network. Table 1 below specifies the end-to end delay calculation of FRA and IWDRA; leading to FRA as the competent winner. Fig. 2 below describes the X graph validation of the proposed approaches.

3.2 Normalized Routing Load (NRL) Calculation of FRA Correlated with IWDRA

With simulation time as the comparison parameter normalized routing load of the proposed FRA and IWDRA approaches is calculated. Normalized routing load is defined as the total number of data packets routed per packets transmitted in an IOT-MANET network. NRL is calculated by dividing the total number of packets sent to the total the total data packets received in a network. Table 2 below specifies the normalized routing load calculation of the two approaches leading to FRA as the competent winner. Fig. 3 below describes the X graph validation of the proposed approaches.

3.3 Packet Delivery Ratio (PDR) Calculation of FRA Correlated with IWDRA

With simulation time as the comparison parameter packet delivery ratio of the proposed FRA and IWDRA approaches is calculated. Packet delivery ratio is defined as the ratio between the data packets received at the destination (D) to the data packets sent by the source (S) in an IOT-MANET network. Packet delivery ratio is considered to be as the most important performance parameter for evaluation in any kind of network. Achieving good ratio of packet delivery leads to optimized performance in MANET. Table 3 below specifies the packet delivery ratio calculation of the two approaches leading to FRA as the competent winner. Fig. 4 below describes the X graph validation of the proposed approaches.

3.4 Packet Loss Ratio (PLR) Calculation of FRA Correlated with IWDRA

With simulation time as the comparison parameter Packet Loss Ratio of the proposed FRA and IWDRA approaches is calculated. Packet Loss Ratio in an IOT-MANET network is calculated as the percentage of loss packets with respect to packets sent. Table 4 below specifies the packet lossratio calculation of the two approaches leading to FRA as the competent winner. Fig. 5 below describes the X graph validation of the proposed approaches.

3.5 Throughput Calculation of FRA Correlated with IWDRA

With simulation time as the comparison parameter throughput of the proposed FRA and IWDRA approaches is calculated. Throughput calculation in an IOT-MANET network is specified with how much data packets are transferred from the source (S) to the destination (D) in a given time. Throughput is considered to be as the most important performance parameter for evaluation in any kind of network. Achieving good ratio of throughput leads optimized performance in MANET. Table 5 below specifies throughput calculation of the two approaches leading to FRA as the competent winner. Fig. 6 below describes the X graph validation of the proposed approaches.

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Table 1. End-to End Delay calculation of FRA and IWDRA

	End to End Delay					
Simulation Time	**100**	**200**	**300**	**400**	**500**	**600**
FRA-ZRP	**0.6**	**0.3**	**0.4**	**0.2**	**0.7**	**0.4**
IWDRA-ZRP	**0.9**	**0.7**	**0.5**	**0.3**	**0.71**	**0.51**

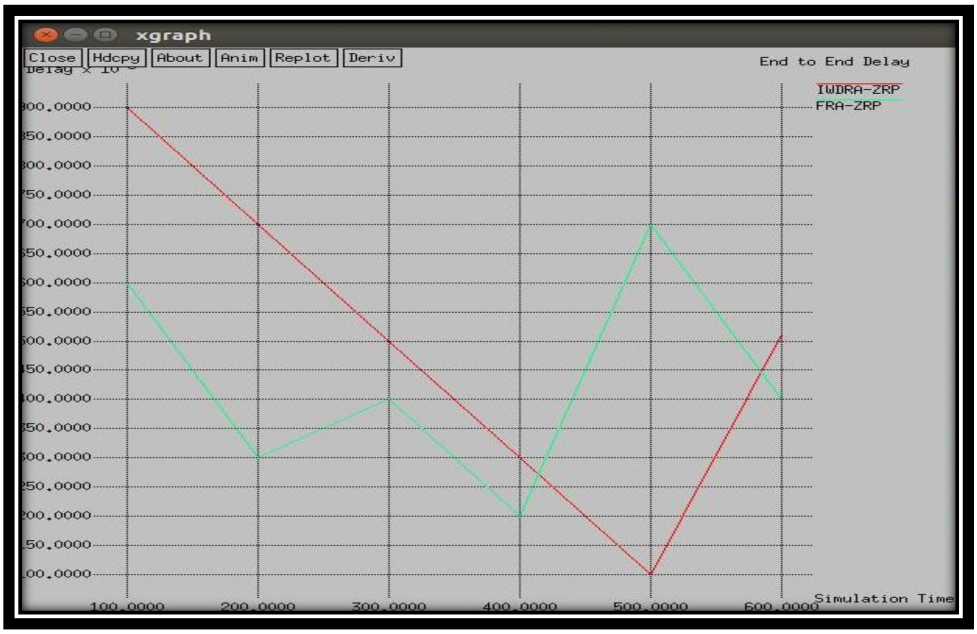

Fig. 2. X Graph results depicting End-to End Delay of the proposed approaches with varying simulation time

Table 2. Normalized Routing Load calculation of FRA and IWDRA

	Normalized Routing Load (NRL)					
Simulation Time	**100**	**200**	**300**	**400**	**500**	**600**
FRA-ZRP	**4.002**	**4.028**	**4.137**	**4.392**	**4.591**	**4.737**
IWDRA-ZRP	**4.009**	**4.031**	**4.154**	**4.927**	**4.625**	**4.923**

Table 3. Packet Delivery Ratio calculation of FRA and IWDRA

	PDR					
Simulation Time	100	200	300	400	500	600
FRA-ZRP	85.9	84.3	87.2	82.4	83	81
IWDRA-ZRP	83.1	81.6	84.2	79.9	78.3	79

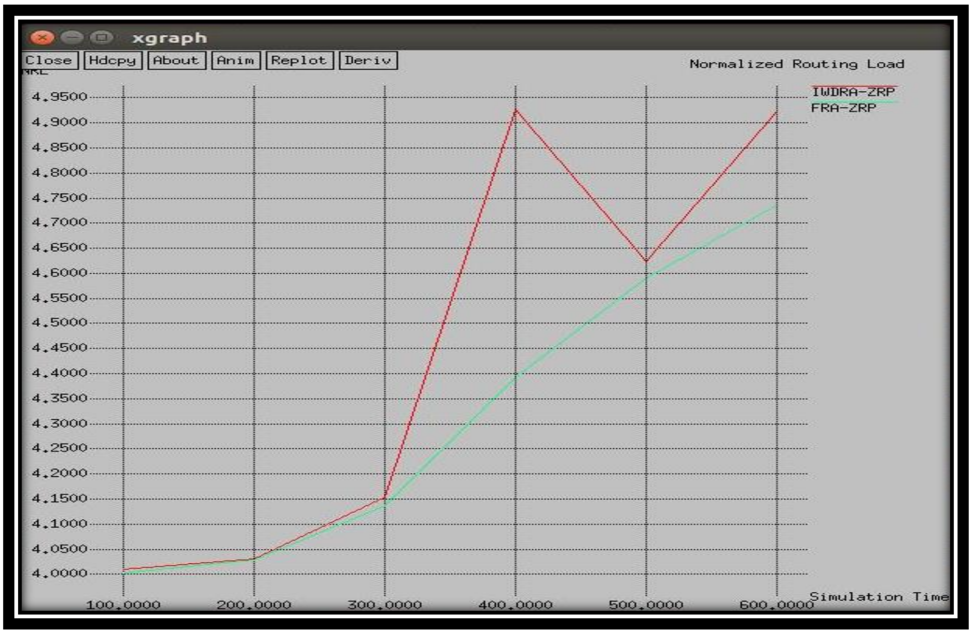

Fig. 3. X Graph results depicting Normalized Routing Load of the proposed approaches with varying simulation time

Table 4. Packet Loss Ratio calculation of FRA and IWDRA

	Packet Loss Ratio					
Simulation Time	100	200	300	400	500	600
FRA-ZRP	14.1	15.7	12.8	17.6	17	19
IWDRA-ZRP	16.9	18.4	15.8	20.1	21.7	21

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Table 5. Throughput calculation of FRA and IWDRA

	Packet Loss Ratio					
Simulation Time	**100**	**200**	**300**	**400**	**500**	**600**
FRA-ZRP	**14.1**	**15.7**	**12.8**	**17.6**	**17**	**19**
IWDRA-ZRP	**16.9**	**18.4**	**15.8**	**20.1**	**21.7**	**21**

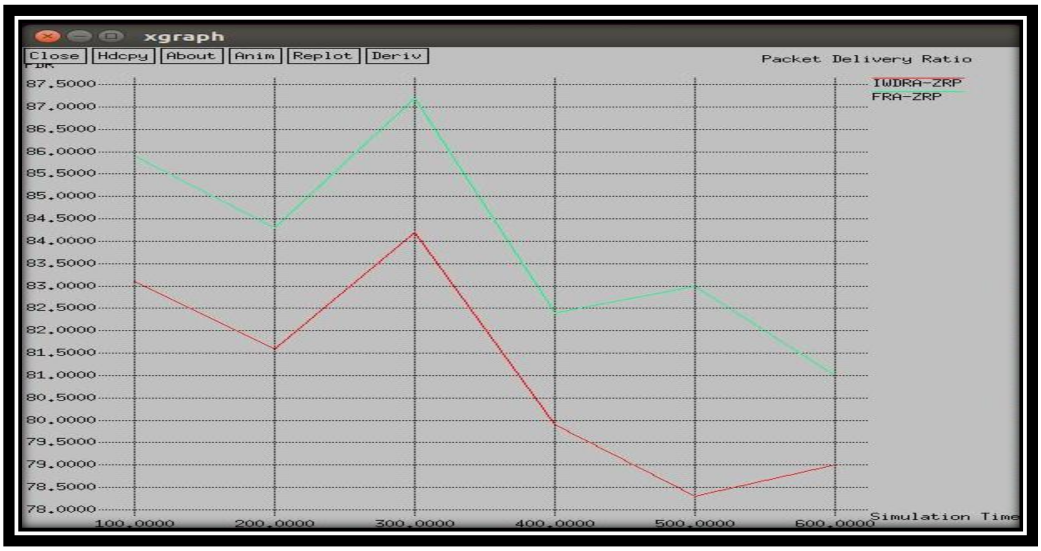

Fig. 4. X Graph results depicting Packet Delivery Ratio of the proposed approaches with varying simulation time

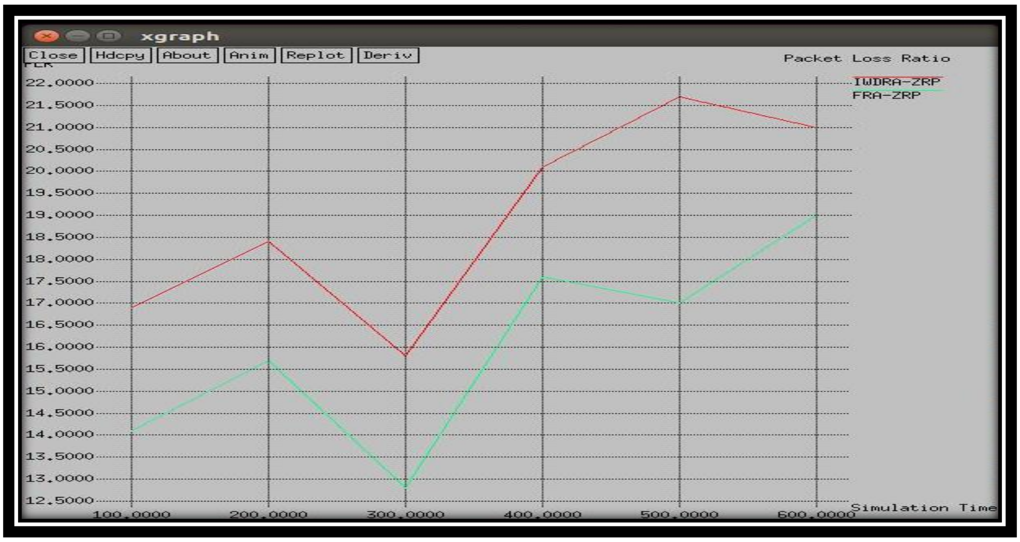

Fig. 5. X Graph results depicting Packet Loss Ratio of the proposed approaches with varying simulation time

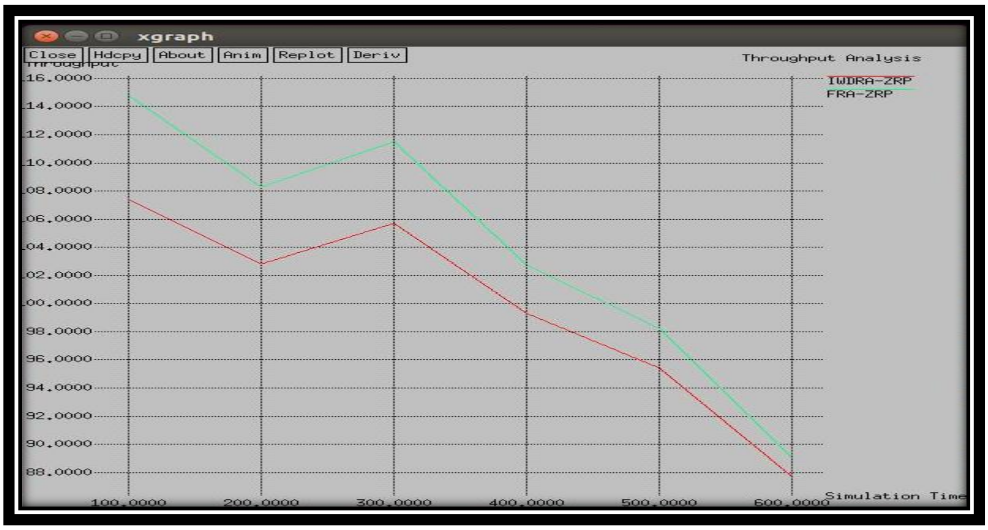

Fig. 6. X Graph results depicting Throughput of the proposed approaches with varying Simulation Time

4. Discussions

The research study conducted through this paper focuses on two most un-talked but most reliable meta-heuristic optimization algorithms, FRA and IWDRA applied in the traditional routing protocol for QOS achievement in MANET which leads to real-time performance accomplishment in IOT-MANET. The routing results of ZRP are not well enough to be utilized in a real time IOT-MANET based solution so QOS improvement and optimization is provided through the ingenious firefly algorithm and intelligent water drop algorithm. But when both the approaches were compared against one another the ingenious firefly algorithm won the race as depicted and validated in section 3. Each node in an IOT-MANET network organizes itself on a hierarchical platform. The simulation results discussed and validated in Section 3 specify that FRA based meta-heuristic approach increases or optimizes QOS lifetime of the nodes around the IOT system.

Since IOT and MANET usually lead to heterogeneous mobile environment the QOS factors are relied upon from source to sink route as each node has different characteristic of dynamical distance, so an objective function is created by the proposed FRA algorithm which eliminates differences of various bound parameters. The FRA objective function is thus utilized for route calculations of various nodes and then optimizes their QOS based performance factors discussed and validated in above Section.

5. Conclusion & Future Work

Meta (upper level) – heuristic (to-find) based firefly and intelligent water drop algorithm guides their subordinate heuristics through combination of intelligent concepts for exploring and exploiting the provided search space and revert back through efficient and near optimal solutions. These algorithms range from a simple local based search procedure to very complex learning process. They have mechanisms which avoids them to get trapped in confined search space areas as they are not problem specific.

Both firefly routing algorithm and intelligent water drop algorithms use previous search experiences to guide their search. This research study has highlighted on optimization of ZRP through FRA and IWD algorithms meta-heuristic in nature. The results validate slight better performance of FRA but it is being specified that both these algorithms in future will be quite effective for real world IOT-MANET based scenarios. Both firefly and IWD algorithms are utilized to solve complex real-life optimization problems by combining constructive methods to escape local minima. These algorithms have features and ability for attacking different applications with diverse requirements. They combine methods for exploring search space, escape local minima and determine optimize solutions for real time applications of healthcare, medical, agriculture etc.

References

[1] Newman, M.E.J. (2004) 'Fast algorithm for detecting community structure in network', Physical Review E, Vol. 69, No. 6, pp.6133–6138.

[2] Newman, M.E.J. (2006) 'Modularity and community structure in networks', Proceedings of the National Academy of Sciences of the United States of America, Vol. 103, No. 23, pp.8577–8582.

[3] Newman, M.E.J. (2006) 'Finding community structure in networks using eigenvectors of matrices', Physical Review E, Vol. 74, No. 3, pp.7821–7826.

[4] Newman, M.E.J. and Girvan, M. (2004) 'Finding and evaluating community structure in networks', Physical Review, Vol. 69, No. 2, pp.26113–26118.

[5] Radicchi, F., Castellano, C., Cecconi, F., Loreto, V. and Parisi, D. (2004) 'Defining and identifying communities in networks', Proceedings of the National Academy of Science of the United States of America, Vol. 101, No. 9, pp.2658–2663.

[6] Girvan, M. and Newman, M.E.J. (2002) 'Community structure in social and biological networks', Proc. Natl. Acad. Sci., Vol.99, No. 12, pp.7821–7826.

[7] I. A. Alameri and G. Radchenko (2017) "Development of Student Information Management System based on Cloud Computing Platform." Journal of Applied Computer Science & Mathematics. 11(2):4-19.DOI:doi.org/10.4316/JACSM.201702001.

[8] M. B. M. Kamel, I. A. Alameri., A. N. Onaizah (2017). "STAODV: A Secure and Trust based Approach to Mitigate Blackhole Attack on AODV based MANET." IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), pp. 1278-1282.

[9] Yang, X-S.: Firefly Algorithm, Stochastic Test Functions and Design Optimization. Int. J. Bio-Inspired Computation, Vol. 2, No. 2, pp.78-84 (2010)

[10] Yang, X-S (2010)"Nature-Inspired Metaheuristic Algorithms" Luniver Press, Beckington, UK, 2nd edition.

[11] Yang, X-S (2009) "Firefly algorithms for multimodal optimization" In: Watanabe O, Zeugmann T, (eds.) Stochastic algorithms: foundations and applications, SAGA 2009, LNCS, vol. 5792, pp. 169–78. Springer-Verlag.

[12] Dorigo, M., Stützle, T.(2004) Ant Colony Optimization, MIT Press.

[13] Dorigo, M., Caro, G. D., Gambardella L. M. (1999). "Ant algorithms for discrete optimization." Université Libre de Bruxelles, Belgium.

[14] Eberhart, R.C., Kennedy, J., Shi, Y. (2001) Swarm optimization. Academic Press.

[15] Eberhart, R.C., Kennedy, J (1995) "Particle Swarm optimization" Proc. of IEEE International Conference on Neural Networks, Piscataway, NJ, pp.1942-1948.

[16] Goldber, D.E (1989) "Genetic Algorithms in Search, Optimization and Machine Learning. Reading" Mass., Addison Wesley.

[17] Heppner, F., Grenander, U (1990) "A stochastic nonlinear model for coordinated bird flocks" The Ubiquity of Chaos. AAAS Publications, Washington DC.

[18] Gautam, Ritu, Prableen Kaur, and Manik Sharma. (2019) "A comprehensive review on nature inspired computing algorithms for the diagnosis of chronic disorders in human beings."Progress in Artificial Intelligence: 1-24.

[19] Mirjalili, Seyedali, and Jin Song Dong. (2020) "Introduction to Nature-Inspired Algorithms." Nature-Inspired Optimizers. Springer, Cham, 1-5.

[20] Kaur, Prableen, and Manik Sharma. (2019) "Diagnosis of Human Psychological Disorders using Supervised Learning and Nature-Inspired Computing Techniques: A Meta-Analysis" Journal of medical systems 43.7: 204.

[21] Lukasik, S., Zak, S.: Firefly algorithm for continuous constrained optimization tasks. R. (eds.), ICCC 2009, Lecture notes in Artificial Intelligence, vol. 5796, pp. 97-100. Springer.

[22] Reynolds, C. W (2009) "Flocks, herds and schools: a distributed behavioral model" Comp. Graph. 25-34 (1987).

[23] Rocha, A.M.C., Fernandes, E.M.G.P., Martins, T.F.M.C (2011) "Novel Fish swarm heuristics for bound constrained global optimization problems" J. Comput. Appl. Math. 235(16), 4611-4620 (2011).

[24] Yang, Xin-She, and Xingshi He. (2013) "Firefly algorithm: recent advances and applications." arXiv preprint arXiv: 1308.3898.

[25] Sharma, M., G. Singh, and R. Singh. (2018) "Clinical decision support system query optimizer using hybrid Firefly and controlled Genetic Algorithm." Journal of King Saud University-Computer and Information Sciences.

[26] Alijla, Basem O., et al. (2014) "A modified intelligent water drops algorithm and its application to optimization problems." Expert Systems with Applications 41.15: 6555-6569.

[27] Wang, Hui, et al. (2018). "A new dynamic firefly algorithm for demand estimation of water resources." Information Sciences 438: 95-106.

[28] Sharma, Manik, Gurvinder Singh, and Rajinder Singh. (2019) "Design of GA and Ontology based NLP Frameworks for Online Opinion Mining." Recent Patents on Engineering 13.2 : 159-165.

[29] Shah-Hosseini, H. (2007). "Problem solving by intelligent water drops', Proceedings of IEEE Congress on Evolutionary Computation." Swissotel, The Stamford, Singapore, pp.3226– 3231.

[30] Shah-Hosseini, H. (2008). "Intelligent water drops algorithm: a new optimization method for solving the multiple knapsack problem." Int. Journal of Intelligent Computing and Cybernetics, Vol. 1, No. 2, pp.193.

[31] Shah-Hosseini, H. (2009). "The intelligent water drops algorithm: a nature-inspired swarm-based optimization algorithm." Int. J. Bio-Inspired Computation, Vol. 1, No. 1, 2, pp.70–71.

[32] Wang, Tao, Jing Ni, and Yixuan Wang. (2019) "An Intelligent Water Drop Algorithm for Solving Multi-Objective Vehicle Routing Problems With Mixed Time Windows." International Journal of Strategic Decision Sciences (IJSDS) 10.1: 82-104.