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Optimised Delay And Basic Safety Messages In Fog Computing Using Extended Grey Wolf Optimisation (Egwo)

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Abstract

Next generation of Fog computing is regarded to be armed with Advanced Fog Node (AFN) along with powerful Artificial Intelligence (AI) and Deep Learning (DL) module. AFN are flexible and energy proficient but the performance is critically affected by inherent frequent data advertisements and overheads for tracking vehicles also termed as basic safety messages. Projected work shows a faster method to select Fog Node for maximum coverage. Grey Wolf Optimisation (GWO) is carefully investigated and particle swarm optimisation (PSO) is projected as an extension to the GWO. The extended GWO is anticipated to accommodate the merits of both the algorithms. EGWO module is capable of addressing receptive and multitude approaches. AFN is selected from the pool of FN's geographically distributed in a given region by the projected optimiser. The problem of optimum FN selection is to maximize coverage considering stationary and random vehicles mapped as a GWO-PSO Optimization (GWO) problem. The results show that the projected fusion algorithm could indeed reduce the computational time and converge very fast by an order, during vehicle tracking.

Keywords- Fog nodes, pso, gwo, optimisation, iterations, coverage and vehicle

1 Introduction

Internet of Vehicle is one of the best choice for tracking and investigation of vehicles because of its elasticity and power efficiency. Intelligent transport system like 5G Vehicular Network, Advanced Fog Node (AFN) develops wireless beacon data to gather information about the vehicular activities but confined to routing protocols [1, 2]. Generally, beacon communication guzzles higher energy than processing it, (e.g. memory, management, sensor sampling, etc.). To manage the energy there is a necessity to implement movement detection tool to accurately decide when to communicate data, in discontinuous mode. For vehicles, the high mobility states occur less frequently and they often spend passively stationary most of the time as the energy supply is limited and difficult to recharge the battery [3]. To save energy, sensor nodes can be turned off or drop their radios wake-up time and in passive state the processor set on a low-power modes. Another way is to use strong computational measures to decide which AFN should be selected to be in active mode and keep rest other AFNs in sleep mode. This search could be exercised using different searching algorithms.

Framework of IoV communication as shown in fig. 1 comprises of three major layer viz. IoV, Fog and Cloud layer. In IoV layer, the Road side unit (RSU) and vehicles are addressed [4, 5]. In fog layer, scheduling-based transmission protocol is executed and in cloud layer, power control mechanisms are investigated [6]. The cloud layer is liable for intelligent data analytics and data prediction for a given application. Scheduling based transmission of fog layer is based on basic safety messages where the initial search and detection of neighbouring vehicle is initialised. The latencies associated with discovery phase of fog layer is very critical as most of the important beacon signals are exchanged between the vehicles and RSUs which quanta mounts overall transmission delay. So there is a need to offload the task by searching an intermediate node that can handle and expedite the discovery phase thereby aborting the route to clouds or central server [7]. Node that is presumed to do the aforesaid task on behalf of Cloud is called Fog Node (FN) and the corresponding computing is called Fog-Computing (FC).

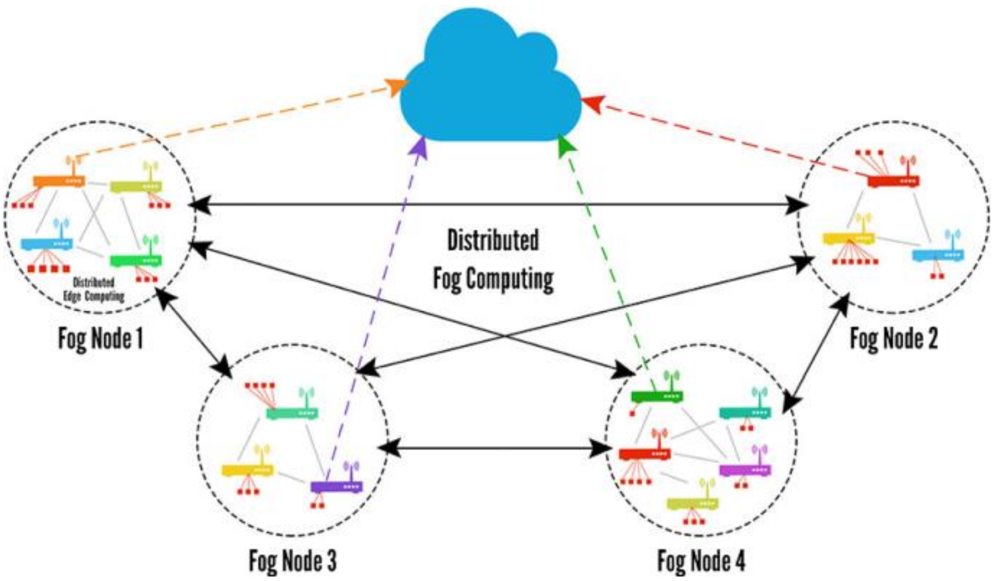


Fig. 1 Distributed fog computing and FN selection

To fetch an optimal AFN for wider coverage the problem is considered as combinatorial optimization problem. It is challenging for simple search techniques to decide the best AFN node & its configuration [8]. Genetic Algorithm (GA) [9] and Particle swarm optimization

(PSO) [10] is used to place camera. Apart from GA and PSO, meta-heuristics approach Grey wolf optimization (GWO) [11] has been used in a variety of fields such as channel estimation in wireless communication [12], photovoltaic systems [13], wireless body area networks [14] and image processing [15]. GWO is stimulated by the behavior of grey wolves to outbreak the prey for hunting and is preferred by leading researchers because of faster convergence rate and robust behavior [11] and [14]. As equated to other optimization algorithms, GWO requires rarer operators and parameters to amend. GA, PSO and ACO (Ant Colony Optimizations are considered much better substitutes for the purpose of selections but GWO outperforms them. The qualities of PSO are also deeply investigated. PSO is an evolutionary optimisation method suggested by Kennedy and Eberhart [16]. Its development was based on observations of the social behavior of vehicles such as birds flocking, fish schooling, and swarm theory [16], [17]. The mechanism of natural progress in evolutionary process is emergent up during last several decades. Common idea for these evolutionary algorithms makes natural selections which is based on environmental pressure and this makes the fitness of population rise.

In Fig 1(a) Many Artificial Intelligence (AI) based approaches have been proposed and developed for link adaptation and optimisation of communication systems. Here Cluster Head (CH) are referred to the fog nodes (FN). Among all the evolutionary algorithms GA and PSO are the well-known algorithms for solving optimisation problems [18]-[20]. Therefore, EGWO is an optimization algorithm for developing a strategy to find the optimal FN and offload the data through this projected AFN. Organisation of the paper is as follows. The paper has 4 sections. explores literature survey is done in Section 2. Proposed architecture is discussed in Section 3 followed by mathematical model. Performance valuation of the projected algorithm-EGWO is described in Section 4 followed by conclusion and references.

2 Literature Survey

The fundamentals of Fog-computing refers to a situation where enormous amount of data is to be offloaded and processed in minimal possible time as shown in fig. 2. The fog communication procedure basically comprises of the detection of vehicles, route, measure the volume of data, process and finally compute to identify a fog node (next to the main server/ cloud) which could reduce the computational load of the server, and achieve a faster reliable communication. First phase is to search candidates for a better fog node from the available nodes/ vehicles moving in a particular Internet of vehicle eco-system. In order to improve the local search ability in 1995, the PSO idea was introduced by Kennedy and Eberharta as shown in fig. 3 (a) where an evolutionary computation technique inspired by swarm intelligence such as birds flocking, fish schooling and even human social behavior [24]. The evolution of several paradigms and an implementation of one of the paradigms is discussed in 1995. In this research benchmark testing of the paradigm was described and applications, including nonlinear function optimisation and neural network training, were proposed with the description of relationships between particle swarm optimisation and both artificial life and genetic algorithms.

PSO simulates different natural phenomena which is a nature inspired algorithm (population based) to address wide range of complications. In the swarm optimisation method the random solutions of the fitness functions are identified as population. The distinct objective functions in the population is known as particle. The new velocity is based on the previous velocity (global best position and local best position) and the position of each particle is updated by a new velocity. A memory in PSO is based on the updated value of the velocity for each particle in each iteration so that the data of good solutions is reserved by all individuals [21].

The particle swarm on social adaptation of knowledge was discussed in 1997 by Dr. Russell. In this paper he focused on past research which made the PSO method more complex and often increases its adaptability to other optimisation problems. He compared the efficacy of the original PSO and the simplified variant with an relaxed technique with tuning their behavioral parameters [22] – [24].

In Grey wolf Optimisation (GWO) [13], the grey wolf alpha (α) is the front-runner in the AFN pack that starts the process. Instructions are given all other wolfs. Other wolves follow the alpha for obeying the directions. The main decisions of entire pack are usually taken by the alpha wolves [25]. Future scope of the paper also provides a platform where different AI based applications may be incorporated viz. rear end collisions, alerts etc. [26]

3 Proposed Extended Architecture – EGWO

In fog computing, the projected fog node behaves like a cluster head (CH) say CH-1,2,3.. etc. as shown in Fig. 2. . The Advanced fog node is analogues to an UAV (Unmanned aerial vehicle) which provides an alternate path / route transfer the data for establishing communication in any particular subnet, under the purview of any o cluster head, say CH-1. Here, any of the CH_i (i=1,2,3,…k) may become the proposed AFN provided it fulfills the criteria of AFN as modeled by EXGWO optimiser. Thus with predefined conditions, its very challenging to search the best AFN. Further key challenge is to track large search space in this distributed mobile ecosystem. The key constraint is to cover all distributed vehicles by a set of FNs i.e. AFN This problem is mapped as an optimization problem. The projected procedure is computationally modest.

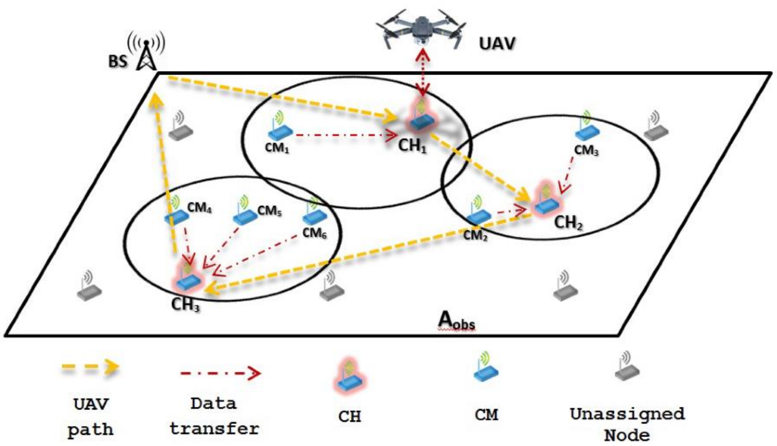
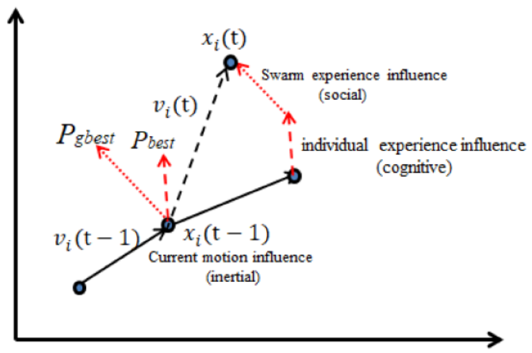


Fig. 2 Advanced fog node based computing

Movement of a vehicle is effectively a random walk since the next move is founded on the current location/state and the transition probability to the next location. Choice of node depends on likelihood that can be molded mathematically. In FCN model, the projected algorithm exploits the merits of PSO and fed to the GWO optimiser rapidly reach to the best fit AFN. Paper shows that any kind of application can be optimized or quality assessment in vehicular environment is achievable with reliability, by an order.

3.1 Methodology of Grey Wolf Optimisation

The projected EGWO algorithm is computationally light and quick for deployment in Internet of vehicles and an integral unit of fog node for reliable execution. The methodology adopted in Fog Computing is to adopt the merits of PSO optimisation and crossbred it with the GWO optimisation as extension. The locations of road side unit (RSU) supporting Visual sensor nodes and the vehicles forms the candidate FNs and constitutes the overall search space. The best fit AFN is from this space of of vehicles and RSU where the choice is computed and selected by the EXGWO. The AFN is projected to have the maximum coverage and better prospects of fog applications like task-offloading with reduced BSMs. The perfomancce of selection is mostly dependent on speed of the optimser. Fig 3 (a) shows how PSO speeds up the optimisation process where as Fig. 3 (b) depicts how GWO reliably reaches to the best AFN by exploring the alternatives form other sets.



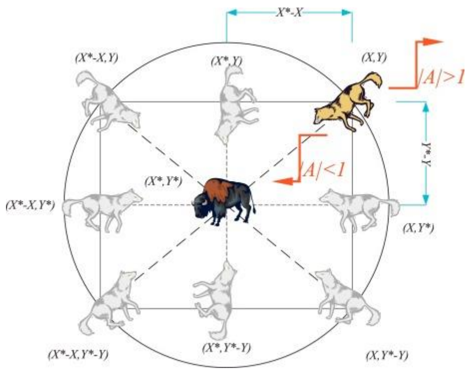


Fig. 3(a) Conventional PSO algorithm

Fig. 3(b) Conventional GWO algorithm

3.2 Decision model using Extended – GWO algorithm (EGWO)

Alpha wolves are considered as the candidate solution for the current oprimisation problem. This set is explored using the projected EGWO search process as shown in fig. 3(b). The position of each wolf is represented by a vector as described in [25]. In this paper the nomenclature and design variable are same for modeling and simulation purpose. Here N represents the number of wolves in the population. The anticipated algorithm – EGWO has the advantages of GWO are crossbred with new projected module for convergence and reach the global best at the earliest as depicted in fig.4.1.

3.3 Projected algorithm for (EGWO)

Advantages of GWO and PSO are clubbed together and the extended –E-GWO optimizer is projected to get AFN selection. Simulated results are obtained built on the following pseudo code.

Start
Prepare alpha, beta, and delta locations
Create dimension, bounds and iterations
Set the no. of fog nodes
Initialize the positions of fog nodes
Get the convergence curve
    For PSO deployment
    Acquire a velocity vector for the search agents
    Get a weight vector (from literature)
    Initialize loop counter =0
    Arrange ascending order of the positions
    Re-set the new location
    While 1< Th_iter
        Return back the fog node agents (Encircle)
        Compute obj. fun. for each fog nonde
        Update Alpha, Beta, and Delta (Exploitation)
        Decrease the surveillance space <2
        Include other solutions/ omega's (Exploration)
        Compute fitness/cost function - sort
        Update the positions of alpha, beta and gamma
        Update the velocity vector as a function of {w,$C_{i,}$,r_i }
        New position as function of {position, velocity}
        Get the final position
        Update the counter
        Reprise the process for best selection
End
Get the convergence curve
Stop

4 Performance Evaluation

Different objective function (F6, F7, F10, F14, F15 and F18) are convex function that are benchmark objective function for testing and getting global best solution. The projected algorithm EGWO is modeled and simulated on MATAB – 2020A computing tool. Total number of fog nodes are 30, no. of variables used 10, maximum no. of Iterations is set to 80, simulation & modeling is completed in MATLAB-2020 A - tool.. No. of fog nodes = 30, Dimension = 2/11, No. variables = 10, Iteration Threshold = 80 and Upper / lower bounds of designed variables are as per the objective function chosen.

4.1 Performance evaluation of GWO optimizer

In the section 3.2, pseudo code for the projected EGWO optimization is shown. Modeling is implemented in MATLAB (version-2020b). Performance analysis of GWO and EGWO optimizer is evaluated in terms of fitness score function using aforesaid simulation conformation, In Fig. 4.1 EGWO optimizer was repeated for 50 iterations. The fitness score of the objective function-F1, is almost converged to zero after 11th iterations. The algorithm congregates rapidly in 40th iteration and the succeeding optimizer coefficient 'a' is speedily reducing after every iteration in fig. 4.2. The target/AFN was hence approached through the EXGWO very closely. In fig.4.3, the search is trying to accommodate new nodes / vehicles to become fog node for reliable communication. This mechanism is termed as exploration. Here the value 'c' referred to as the exploration constant. Overall objective function is minimized at a much faster rate, in fig. 4.4.

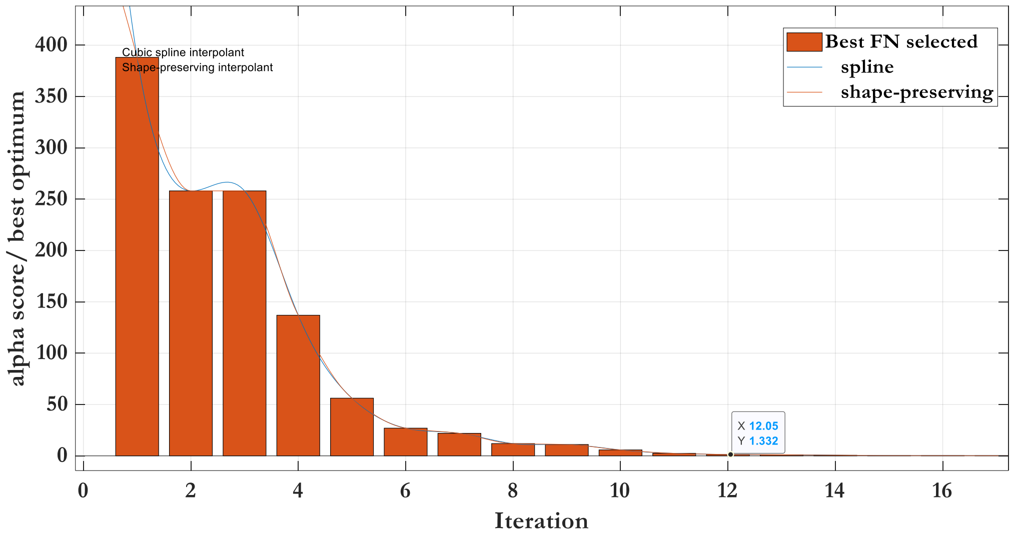


Fig.4.1 Optimiser's fitness value - FN Iteration

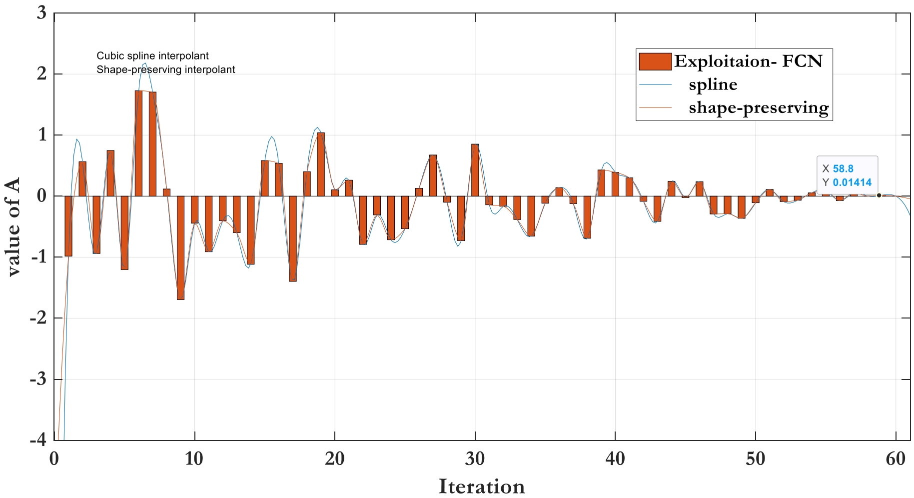


Fig.4.2 convergence after every iteration (best AFNs)

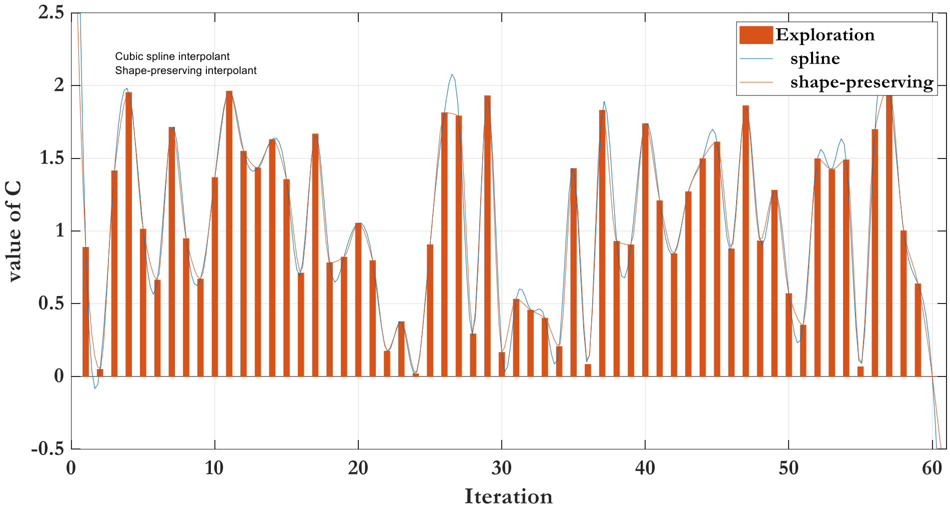


Fig.4.3 Inclusion of new FN for exploration in FCN

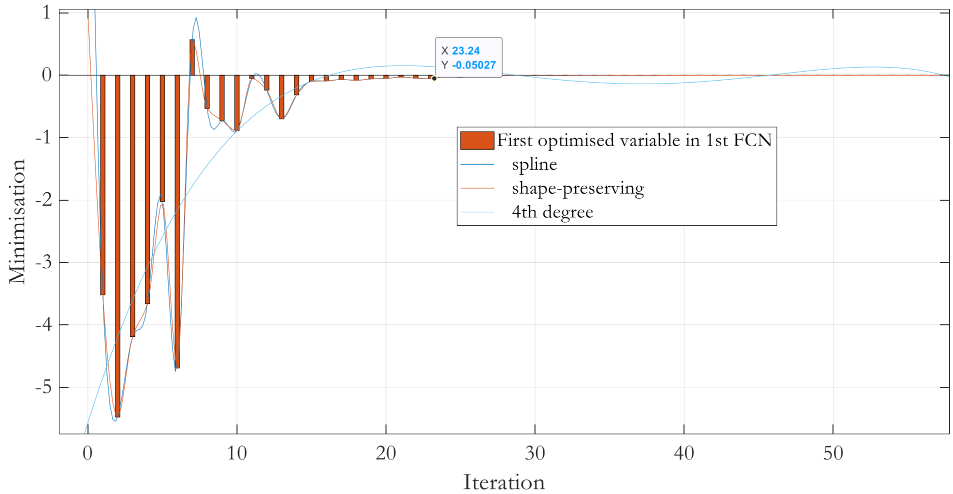


Fig.4.4 Minimisation of objective function for better FN in FCN

4.2 Result and discussion

The proposed extended optimisation algorithm - EGWO is simulated according to the configuration discussed in section 3. The performance analysis of EGWO algorithm is matched with conventional GWO optimizer. The proposed algorithm is simulated for 80 iterations. Objective function – F6 is modeled and shown in fig. 4.5 (b), the projected algorithm outclasses the GWO algorithm. Algorithms congregates with the rise in iterations but GWO is confined near the local optima whereas EGWO and reduces the fitness score. Inclination and breach near 10^{th} iteration noticeably displays global best (sub-optimal) solution attained by EGWO. In fig. 4.6(b) to fig. 4.10 (b), it is witnessed the fitness score of the objective functions-(F6/F7/F10/F14/F15 & F18) - is decreased exponentially (between 20 to 40) with the increase in number of iteration, for the projected model –EGWO and performs better as compared to the conventional GWO optimser.

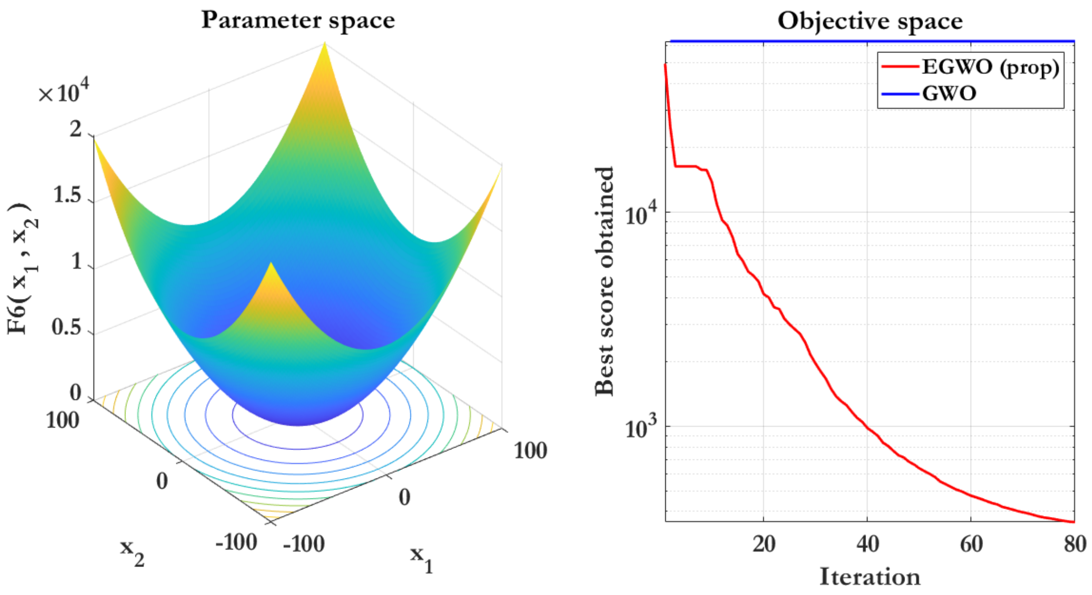


Fig.4.5 (a) F6- Convergence of search space (b) Optimal score of EGWO-FN

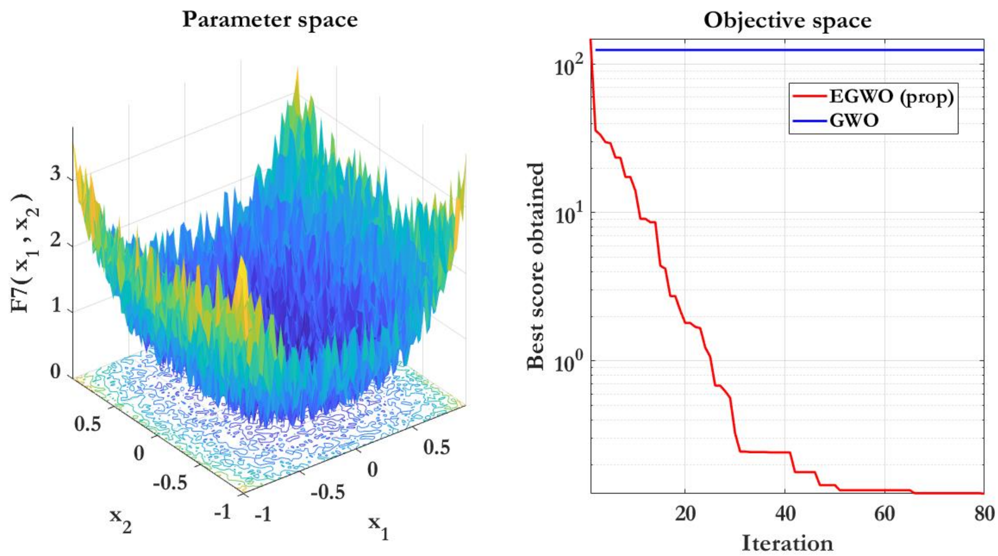
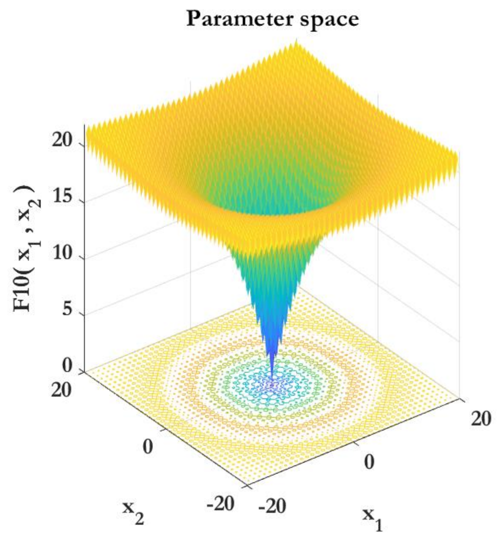


Fig.4.6 (a) F7- Convergence of search space (b) Optimal score of EGWO-FN



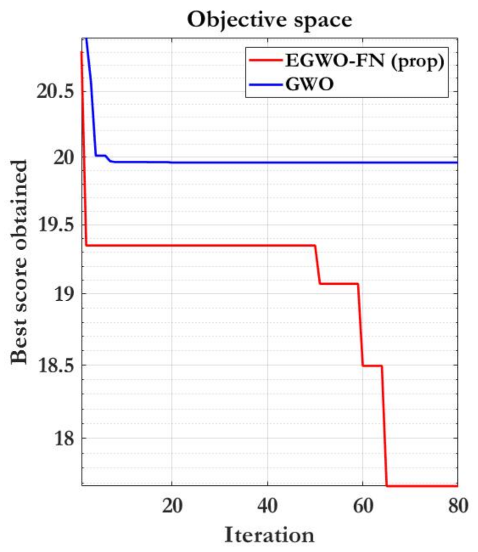
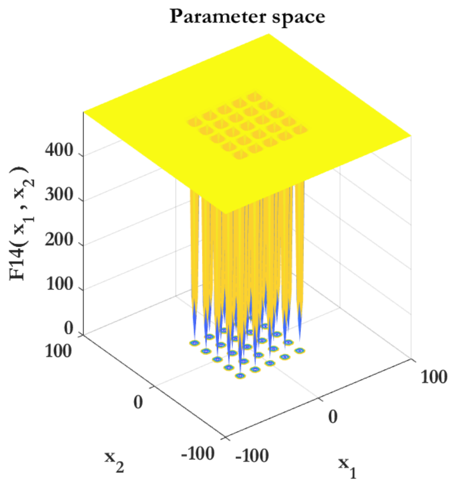


Fig.4.7 (a) F10- Convergence of search space (b) Optimal score of EGWO-FN



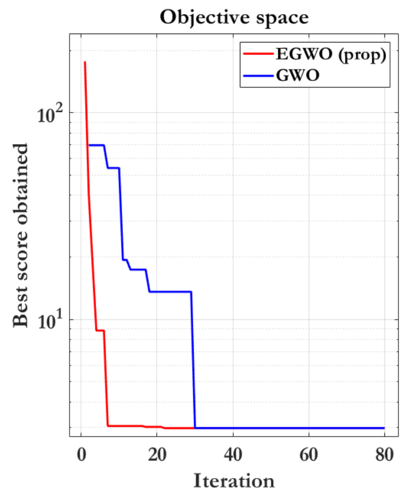
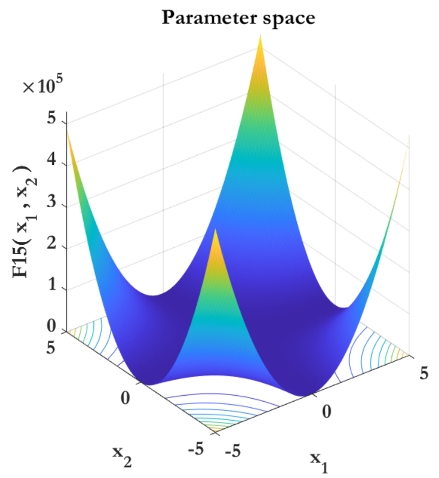


Fig.4.8 (a) F14- Convergence of search space (b) Optimal score of EGWO-FN



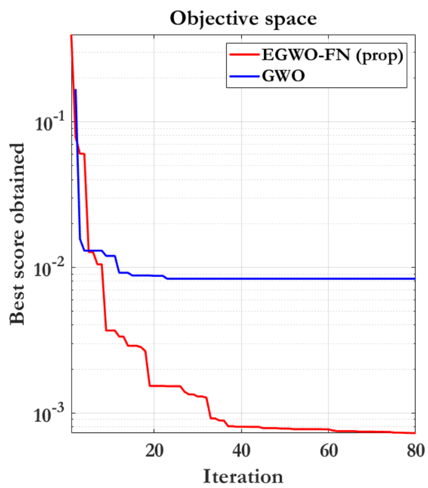


Fig.4.9 (a) F15- Convergence of search space (b) Optimal score of EGWO-FN

EGWO algorithm is matched with GWO optimiser and performance comparison is established . The proposed algorithm quickly touches to the solution i.e. reaches to the target solution very fast through less number of iterations. In Fig 4.9 (b), at 7th iteration, there is a cross-over in performance, but later GWO is settled with local optimal solution whereas EGWO gets a minimized cost (fitness score value) in additional fewer iterations. In Fig. 4.3 (b) and 4.4 (b) large gap is observed in performance for EGWO and GWO optimiser. In most of the rastrigian functions used, the projected EGWO algorithm out accomplishes the GWO algorithm, almost by an order. In Fig. 4.8 (b) and Fig. 4.9 (b) the fitness score is almost 10 times reduced say at 5th and 10th iteration resp. The minimum number of iterations required to compute the best FN by proposed EGWO is 6 iterations (unlike 30 iterations of GWO) that is almost 80 % less time as compared to the traditional GWO. This not only eliminates the redundant overheads and basic safety messages being transmitted to fetch the best fit FN from neighbors but also saves the transmission power in discovery phase, proportionately. When this architecture is installed in an Internet of vehicle eco-system for the purpose of traffic data collection and surveillance, the proposed algorithm can quickly locate/suggest the best FN to be in active state and keep other in passive mode. During a failure of any specific FN, for uninterrupted communication a new FN is required. Proposed EGWO quickly quests the new FN (substitute) and the application could be restored.

When the services/ application is disrupted due to channel or system impairments then urgently an alternate AFN is required to resume the connection. Therefore the choice of alternate FN (alpha wolf) must be very fast to track the dynamic movement of the vehicles. The proposed optimisation procedure is used for localization and tracing of vehicles, it escapes the local optimal solutions and returns with global sub-optimal solution through lesser number of iterations.

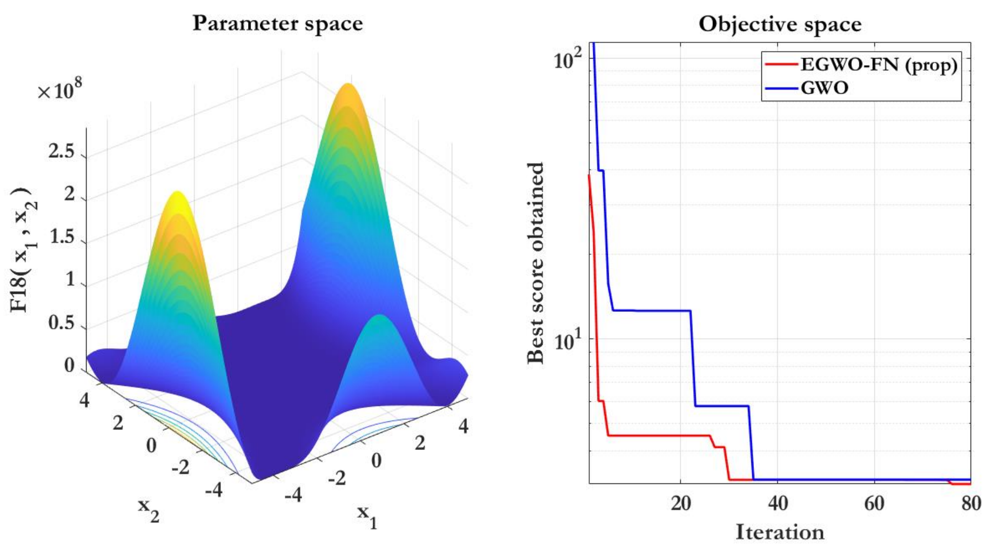


Fig.4.10 (a) F18- Convergence of search space (b) Optimal score of EGWO-FN

Conclusion

Optimization of the coverage and computational time of an advanced fog node from a set of eligible FN is projected as an Optimisation problem. by adjusting their locations, using an extended-meta-heuristic algorithm - EGWO. The proposed EGWO procedure is computationally lighter and quicker in execution. Internet of vehicle ecosystem is mapped to search space, vehicles and feasible RSU are considered as suitable candidate for better FN tracking application. The evaluation provides that the energy consumption and the battery (node) life is also upgraded by an order as lot of energy is utilised primarily when beacon signals are communicated for a superior search by an order. Lesser number of iterations indicates significant saving in computational time (delay) and related power. The prototype also delivers a scope for Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL) modules to control the numerous aspects of fog computing viz. obstacles, and feasible camera locations. The anticipated work gives a low-cost and economical solution for reliable fog computing. From the investigation, the projected EGWO yields less number of iterations and congregate at a faster rate.

Future work

This paper delivers a prototype to accommodate AI, ML and DL modules which may increase the performance of Fog-computing to another level. In future effort may be stretched to predictive analytics for extensive variety of application yielding better Quality of Service (QoS).

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