Deployment of Multi-tier Fog Computing System for IoT Services in Smart City

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***Abstract*—One of the assuring technologies today is Fog computing, focus on the extensive use of the computational and storage capacities of the end devices in a network. In present day there due to the enormous amount of data from the number of IoT devices, a centralized cloud system is quite inadequate. This challenge can be addressed by deploying Fog devices neighbouring to these IoT devices so as to provide with real-time response. Thus for the creation of a smart city we advance towards an architecture in which the cloud data centre at the top followed by SDN controllers, fog controllers, fog devices and smart sensors. We propose an integer programming model in our problem formulation of deploying the fog nodes, fog controllers, SDN controllers which results in minimization of latency, traffic and cost with constraints such as device capacity, offloading workload, range etc. Further on, our work solve this NP-hard problem by weighted sum method and the two meta-heuristic algorithms Genetic Algorithm (GA), Particle Swarm Optimization (PSO) compared to Randomized Algorithm. Thus a network planner with a cost efficient fog network in mind can relate to the simulations illustrated in the paper for their existing computational and storage configuration. We verify our proposed model and algorithms through simulation which help to design efficient fog network.**

***Index Terms*—Fog Computing, IoT services, Smart city, Meta-heuristic algorithm, Fog Network Design**

I. INTRODUCTION

With the massive growing urban population, problems such as traffic, pollution, health issues, congestion, low quality of general services has shown a rapid growth. To tackle these problems smart city is a solution is being propounded by everyone. Smart city is an formidable vision as to resolve the above urbanization problems by the efficient use of the city infrastructure thus improving the life sustenance of its citizens. With the latest advances in the technologies such as Internet of Things (IoT), fast communication and efficient networking, computing and big data analytics the dream of smart city can be achieved. Problems related to the areas such as health-care, traffic, water, energy, waste management can be solved. IoT supplies a robust instrument to sense and control the physical city surroundings [1]–[3]. Data analytics of the information generated by these IoT devices is a key in attaining and redeeming the city smartness. Clouds being a virtually unlimited source of storage and computational resource, are thought to be a environment for the big data analytics[4] [5] and can easily manage the IoT devices. The amount of IoT devices in our surrounding is around 7 billion, and expected to reach a cosmic count of 10 billion by 2020. We can imagine the amount of data that these devices would be generating so as to bottleneck the capacity of the cloud centres working around them. Thus applications which require fast real-time response for the safety and emergency issues are not addressed in an optimal way. Problem arises especially with the wireless network, as they have low bandwidth and high functional costs. Although many edge device computing model exists such as Cloudlet, mobile edge computing and fog computing are proposed to address this issue on a large [3], [6]–[9]. The essence of these technologies is that of bringing the computing and the caching properties, resources and analytical power nearer to the places where this data is being generated. Some of these technologies such as cloudlet; mobile edge computing and fog radio access networks which are provided by third parties are at fixed locations-based solution, which are quite powerful yet not adaptable enough for on demand deployment when there is a requirement. Even the bottleneck problems of the wireless network due to huge data generation by the IoT devices are quite prevalent. Due to these reasons only fog computing has opened for research and development, still being at very early stage. WiFi access points and smartphones computational capabilities [3], [8] can be utilized for the analytical purposes when they are available and required. Processing on these computing devices is suitable only for time-sensitive data. Big data analytics and large time consuming computation happens on the centralized cloud only. The primitive fog computing model did not resolved large scale data analytics challenges faced by IoT applications. Due to the technological advancement in the last few years has given a boom in the smart devices such as (e.g. smart phones and tablets).With an increased computational power, communication and storage capabilities of these devices, small ad-hoc fogs can be formulated. Even small base stations and WiFi based hotspots are also gaining popularity. These small base stations can contain dedicated computing resource to form a macro-level base station to design fog network.

With the varying requirement of the smart cities, leads to multi-tier fog infrastructure so that the QoS management of these multi-layered fogs can correlate each other with a remote cloud in delivering a productive and immediate response. In the current paper we propose a mutli-level fog computing based, broad scale data analytics utility service for

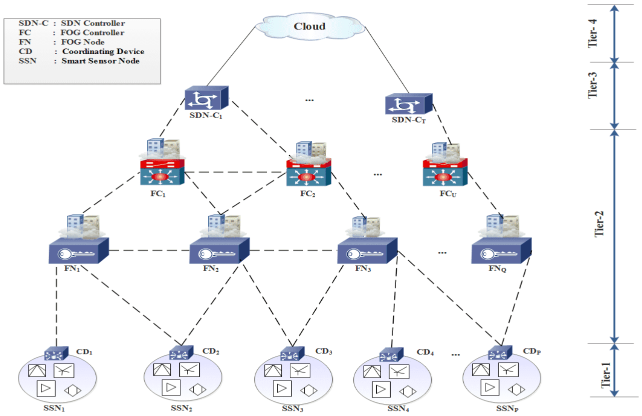

Fig. 1: Hierarchical Architecture of Fog System Model

the smart cities. Basically there are three main contributions: A framework of multi-tier fog computing is proposed, which is composed of both ad-hoc and dedicated fogs with unique deployable resources. Massive initial infrastructure of fog can be neglected by utilizing the opportunistic and radially available computing resources. The distributed computing engines abet in large scale data analytics services over the proposed multi-tier fog computing system. Smart city that has multiple applications which utilizes admission control, offloading, QoS and resource allocation with an aim of providing real-time data analytics which in turn enhances the utility of fog computing. The QoS constraints of real-time jobs and improving the computing utility is achieved by acknowledging the bandwidth, latency, cost and computation of the Network. To the best of our knowledge, QoS issues for fog computing has rarely been touched in the literature.

II. System Model and problem formulation

Fig 1 depicts the hierarchy and the connection architecture of the fog nodes with the above fog controller and SDN controller with a crucial aim of reducing distribution cost with constraints of high demand capacity, coverage and volume of the devices. Table 1 describe the notations used in the problem model.

Objective:- The model is relevant according to the IP model:

$$\begin{aligned} Cost_{Fog\_Netw} = {} & C_f \sum_{(i,j)\in\{I\}\times\Phi_{SC}} x_{ij}.d_{ij} + C_{SC} \sum_{m\in\Phi_{SC}} sc_m + \\ & C_{FC} \sum_{n\in\Phi_{FC}} fc_n + C_F \sum_{t\in\Phi_F} f_t \end{aligned} \tag{1}$$

$$\begin{aligned} Delay_{Trans} = {} & \sum_{k\in\Phi_C} \sum_{t\in\Phi_F} x_{tk}\,\alpha + \sum_{t\in\Phi_F} \sum_{n\in\Phi_{FC}} x_{nt}\,\alpha + \\ & \sum_{n\in\Phi_{FC}} \sum_{m\in\Phi_{SC}} x_{mn}\,\alpha + \sum_{m\in\Phi_{SC}} \sum_{I} x_{\mathrm{Im}}\,\alpha \end{aligned} \tag{2}$$

$$\begin{aligned} Delay_{\mathrm{Pr}\,op} = {} & \sum_{k\in\Phi_C} \sum_{t\in\Phi_F} x_{tk}\,\beta + \sum_{t\in\Phi_F} \sum_{n\in\Phi_{FC}} x_{nt}\,\beta + \\ & \sum_{n\in\Phi_{FC}} \sum_{m\in\Phi_{SC}} x_{mn}\,\beta + \sum_{m\in\Phi_{SC}} \sum_{I} x_{\mathrm{Im}}\,\beta \end{aligned} \tag{3}$$

$$\begin{aligned} Delay_{\mathrm{Pr}\,o} = {} & \sum_{k\in\Phi_C} \sum_{t\in\Phi_F} x_{tk}\,\delta + \sum_{t\in\Phi_F} \sum_{n\in\Phi_{FC}} x_{nt}\,\delta + \\ & \sum_{n\in\Phi_{FC}} \sum_{m\in\Phi_{SC}} x_{mn}\,\delta + \sum_{m\in\Phi_{SC}} \sum_{I} x_{\mathrm{Im}}\,\delta \end{aligned} \tag{4}$$

$$Delay_{Fog\_Netw} = Delay_{Trans} + Delay_{\mathrm{Pr}\,op} + Delay_{\mathrm{Pr}\,oc} \tag{5}$$

$$\begin{aligned} Traffic_{Fog\_Netw} = {} & \sum_{k\in\Phi_C} \sum_{t\in\Phi_F} (L_C \times \Psi_C) + \\ & \sum_{t\in\Phi_F} \sum_{n\in\Phi_{FC}} (L_F \times \Psi_F) + \sum_{n\in\Phi_{FC}} \sum_{m\in\Phi_{SC}} (L_{FC} \times \Psi_{FC}) \end{aligned} \tag{6}$$

$$\begin{aligned} FCS\_Network = {} & Cost_{Fog\_Netw},\ \ Delay_{Fog\_Netw}, \\ & Traffic_{Fog\_Netw} \end{aligned} \tag{7}$$

$$Minimize(FCS\_Network) \tag{8}$$

subject to (9)-(33)

Constraints required in building the network for the whole architecture in a bottom-up fashion are here by illustrated. Constraint (9) enforces that for each coordinating device k, only one link x_{tk} between fog node t and co-ordinating device k is connected.

$$\sum\nolimits_{t\in\Phi_F} x_{tk} = 1, \quad \forall k \in \Phi_C \tag{9}$$

Constraints (10) and (11) consider the binary decision variable f_t of whether to deploy a fog device t is determined by the links with co-ordinating devices.

$$f_t \le \sum\nolimits_{k\in\Phi_C} x_{tk}, \quad \forall t \in \Phi_F \tag{10}$$

$$x_{tk} \le f_t, \quad \forall t \in \Phi_F, \quad \forall k \in \Phi_C \tag{11}$$

Constraints (12) imposes that specifically one fog controller n coupled with fog node t.

$$\sum\nolimits_{n\in\Phi_{FC}} x_{nt} = f_t, \quad \forall t \in \Phi_F \tag{12}$$

Similarly, constraints (13)-(15) determine binary decision variable fc_n of whether to place a fog controller n.

$$fc_n \le \sum\nolimits_{t\in\Phi_F} x_{nt}, \quad \forall n \in \Phi_{FC} \tag{13}$$

$$x_{nt} \le fc_n, \quad \forall n \in \Phi_{FC}, \quad \forall t \in \Phi_F \tag{14}$$

$$\sum\nolimits_{m\in\Phi_{SC}} x_{mn} = fc_n, \quad \forall n \in \Phi_{FC} \tag{15}$$

TABLE I: Definitions of Notations

Parameter	Definition	Parameter	Definition
I	Cloud data center Index	Φ_{SC}	set of possible locations of SDN controllers.
Φ_{FC}	set of possible locations of fog controllers.	Φ_F	set of possible locations of fog nodes.
Φ_C	set of co-ordinating node.	C_f	The cost of unit length of fiber.
C_{SC}	set up cost of a SDN controller.	C_{FC}	set up cost of a fog controller.
C_F	set up cost of a fog node.	α	method that measure transmission delay.
β	method that measure propagation delay.	δ	method that measure processing delay.
D_m^{SC}	The maximum capacity that SDN controller m can meet.	D_n^{FC}	The maximum capacity that fog controller n can meet.
D_t^F	The maximum capacity that fog node t can meet.	N_{SC}	The upper limit of the number of fog controllers regulated by a SDN controller.
N_{FC}	The upper limit of the number of fog devices regulated by a fog controller.	N_F	The upper limit of the number of coordinating devices which are covered by a fog device.
d_{ij}	Distance between node i and node j.	L_C	The length of data to be transferred from a coordinating device to a fog device.
L_F	The length of data to be transferred from a fog device to a fog controller.	L_{FC}	The length of data to be transferred from a fog controller to a SDN controller.
Ψ_C	The data rate from a co-ordinating device to a fog device.	Ψ_F	The data rate from a fog device to a fog controller.
Ψ_{FC}	The data rate from a fog controller to a SDN controller.	R_F	Diameter of the coverage range of a fog device.
R_{FC}	Diameter of the coverage range of a fog controller.	R_{SC}	Diameter of the coverage range of a SDN controller.
θ_C	Demand of a co-ordinating device.	ϕ_{tk}^F	Maximum time is taken to establish the link between fog device t and coordinating device k.
ϕ_{nt}^{FC}	Maximum time is taken to establish the link between fog controller n and fog device t.	ϕ_{mn}^{SC}	Maximum time is taken to establish the link between SDN controller m and fog controller n.
$\varpi(P_i)$	Demand of possible location P_i.		
x_{ij}	A binary decision variable deciding if a link between nodes i and j exists.	sc_m	A binary decision variable deciding if the possible location for SDN controller m is selected to place a SDN controller.
fc_n	A binary decision variable deciding if the possible location for fog controller n is selected to place a fog controller.	f_t	A binary decision variable deciding if the potential site for fog device t is selected to place a fog device.

Constraints (16)-(18) define binary decision variable sc_m of whether to deploy a SDN controller m.

$$sc_m \leq \sum\nolimits_{n\in\Phi_{FC}} x_{mn}, \quad \forall m \in \Phi_{SC} \tag{16}$$

$$x_{mn} \leq sc_m, \quad \forall m \in \Phi_{SC}, \quad \forall n \in \Phi_{FC} \tag{17}$$

$$x_{\mathrm{Im}} = sc_m, \quad \forall m \in \Phi_{SC} \tag{18}$$

Constraints towards the needed capacity of every device are described as listed below. Constraint (19) enforce the needed amount $\varpi(f_t)$ provided by fog device t to be all requirement of all coordinating devices resolutions with all the connections between fog node t and each coordinating node k; and constraints (20) imposes that the maximum capacity D_t^F for a fog device t.

$$\sum\nolimits_{k\in\Phi_C} \theta_C.\ x_{tk} = \varpi(f_t), \quad \forall t \in \Phi_F \tag{19}$$

$$\varpi(f_t) \leq f_t.\ D_t^F, \quad \forall t \in \Phi_F \tag{20}$$

Constraints (21)-(22) consider the maximal demand D_n^{FC} for a fog controller n, and Constraints (23)-(24) take into account the limit of D_m^{SC} for a SDN controller m.

$$\sum\nolimits_{t\in\Phi_F} \varpi(sc_m).\ x_{nt} = \varpi(fc_n), \quad \forall n \in \Phi_{FC} \tag{21}$$

$$\varpi(fc_n) \leq fc_n.\ D_n^{FC}, \quad \forall n \in \Phi_{FC} \tag{22}$$

$$\sum\nolimits_{n\in\Phi_{FC}} \varpi(fc_n).\ x_{mn} = \varpi(sc_m), \quad \forall m \in \Phi_{SC} \tag{23}$$

$$\varpi(sc_m) \leq sc_m.\ D_m^{SC}, \quad \forall m \in \Phi_{SC} \tag{24}$$

Constraints (25)-(27) does the estimation of the latency times between fog device t and coordinating device k , between fog controller n and fog device t, and between SDN controller m and fog controller n, and enforce them not to be exceed the maximal latency times ϕ_{tk}^F, ϕ_{nt}^{FC}, and ϕ_{mn}^{SC} respectively.

$$L_C/(\sum\nolimits_{k\in\Phi_C} x_{tk}.\Psi_C).f_t \leq \phi_{tk}^F, \quad \forall t \in \Phi_F \tag{25}$$

$$L_F/(\sum\nolimits_{t\in\Phi_F} x_{nt}.\Psi_F).fc_n \leq \phi_{nt}^{FC}, \quad \forall n \in \Phi_{FC} \tag{26}$$

$$L_{FC}/(\sum\nolimits_{n\in\Phi_{FC}} x_{mn}.\Psi_{FC}).sc_m \leq \phi_{mn}^{SC}, \quad \forall m \in \Phi_{SC} \tag{27}$$

Number of links for each fog device, fog controller, and SDN controller has a limit in constraints (28)-(30), respectively.

$$\sum\nolimits_{k\in\Phi_C} x_{tk} \leq N_F, \quad \forall t \in \Phi_F \tag{28}$$

$$\sum\nolimits_{t\in\Phi_F} x_{nt} \leq N_{FC}, \quad \forall n \in \Phi_{FC} \tag{29}$$

$$\sum\nolimits_{n\in\Phi_F C} x_{mn} \leq N_{SC}, \quad \forall m \in \Phi_{SC} \tag{30}$$

For wireless links between fog devices and coordinating devices, fog controllers and fog devices, SDN controllers and fog controllers ,constraints (31)-(33) considers that the distance between fog devices and coordinating devices, fog controllers and fog devices, and SDN controllers and fog controllers must not be exceed the coverage range R_F, R_{FC}, and R_{SC}, respectively.

$$x_{tk}.d_{tk} \leq R_F/2, \quad \forall t \in \Phi_F, \quad \forall k \in \Phi_C \tag{31}$$

$$x_{nt}.d_{nt} \leq R_{FC}/2, \quad \forall t \in \Phi_F, \quad \forall n \in \Phi_{FC} \tag{32}$$

$$x_{mn}.d_{mn} \leq R_{SC}/2, \quad \forall n \in \Phi_{FC}, \quad \forall m \in \Phi_{SC} \tag{33}$$

III. Proposed algorithm

There are possible numbers of approaches for the solution of a multiple objective problem, and the most evident solution is to solve it is by converting it to single one. It is carried out by weighted sum technique.

A. Weighted Sum Method

The weighted sum approach combines multi-objective functions into a scalar main objective function. In this combination, different objectives are given weight values between 0 and 1. The proposed objective function can be rewritten using the following equations:

$$Minimize \left(\begin{array}{l} w_1.\, Delay^{norm}_{Fog\_Netw} + w_2.\, Traffic^{norm}_{Fog\_Netw} \\ + w_3.\, Cost^{norm}_{Fog\_Netw} \end{array} \right) \tag{34}$$

where w_1, w_2, and w_3 are weighted coefficients and $Delay^{norm}_{Fog\_Netw}$, $Traffic^{norm}_{Fog\_Netw}$, $Cost^{norm}_{Fog\_Netw}$ are the normalized objective functions as they have different scales. Equations (34)-(36) are used to normalize the objective function. An additional constraint (37) is added which states that the sum of the weighted coefficients should be 1.

$$Delay^{norm}_{Fog\_Netw} = \frac{Delay^{\max}_{Fog\_Netw} - Delay_{Fog\_Netw}}{Delay^{\max}_{Fog\_Netw} - Delay^{\min}_{Fog\_Netw}} \tag{35}$$

$$Traffic^{norm}_{Fog\_Netw} = \frac{Traffic^{\max}_{Fog\_Netw} - Traffic_{Fog\_Netw}}{Traffic^{\max}_{Fog\_Netw} - Traffic^{\min}_{Fog\_Netw}} \tag{36}$$

$$Cost^{norm}_{Fog\_Netw} = \frac{Cost^{\max}_{Fog\_Netw} - Cost_{Fog\_Netw}}{Cost^{\max}_{Fog\_Netw} - Cost^{\min}_{Fog\_Netw}} \tag{37}$$

$$w_1 + w_2 + w_3 = 1 \tag{38}$$

The main aim of our aforementioned work is to considered matrices must be optimized as to place the FNs, FCs, and SDN-Cs $(k, t, m\; respectively)$ nodes in the network. We have used fitness function and objective function interchangeably. The euclidean distance is used as a distance matrix for the algorithms which is calculated by the latitudes and longitudes of nodes.

The FND_Random algorithm selects randomly k FNs from the total n possible locations, t FCs from k possible locations and m SDN-C from t possible locations. Finally, the Algorithm 1 produces the fitness function and the final positions of the FNs, FCs and SDN-Cs. A sub-optimal solution of the objective function is obtained by the FNs', FCs' and SDN-Cs' position vector in the proposed FND_PSO algorithm. We assume d dimensional vectors of the n particles each being a potential solution. The proposed algorithm finds the best solution from a population called swarm. Upon the use of the two types of learning that is cognitive and social learning our algorithm find the best solution amongst the many. The position of the FNs is represented by each of the dimension, where a given number FNs k, each particle P_i is described as a $k - dimensional$ vector. Permutation of a particle is described as $P_i = \{P_{i1}, P_{i2}, \ldots\ldots., P_{ik}\}$ and $P_{ik} \in [1, n]$, when n is the number of nodes in the network. Similarly, we can find out FCs' position and SDN-Cs' position. In our algorithm a network represented by G where the weight of an edge represents the distance between two nodes. The algorithm with a random permutation of FNs initializes each particle's position vector among the total number of the nodes. Similarly happens for FCs and SDN-Cs. Each particle's velocity in x a,d y components are initialized to zero and even the particle's global velocity too. Updating the fitness of the particle in each iterations. If newly obtained fitness value is better than the previous fitness value of the particle, then its fitness value is updated.

The Algorithm 3 operates on the fitness population of chromosomes and each chromosome is a collection of FNs positions. The best possible FNs, FCs, and SDN-Cs location using GA can be obtained by setting various generic operators such as crossover, mutation, stopping criteria, etc. The algorithm simulates on the basis of "survival of the fittest" type scenario, where each generation of the algorithm attempts to improve upon previous generation.

Algorithm 1: FND_Random

Input: $coordinates\_nodes(x, y)$, No_FN, No_FC, No_SDN_C

Output: $cost$, $position$

```
for i = 1 to No_FN do
    R_{FN_position} ←
      Random (coordinates_nodes (x, y) , No_FN)
    KMeans_Clustering (coordinates_nodes (x, y), R_{FN_position})
    FN_Position ← Centroid of each cluster
for i = 1 to No_FC do
    R_{FC_position} ←
      Random (coordinates_FNs (x, y) , No_FC)
    FC_position ← R_{FC_position}
for i = 1 to No_SDN_C do
    R_{SDN_C_position} ←
      Random (coordinates_FCs (x, y) , No_SDN_C)
    SDN_C_position ← R_{SDN_C_position}
Calculate FCS_Network
return FCS_Network, positions
```

IV. Implementation and simulation results

In this paper, we define the group of IoT devices cluster which has a unique IP address. Each cluster has its own

Algorithm 2: FND_PSO

Input: $co\_ordinates\_nodes(x, y)$, No_FN, No_FC, No_SDN_C

Output: $cost$, $position$

A population of nodes vector which are randomly generated, local velocity vector (L_v) and global velocity vector (G_V), and velocity vector (V) for each particle in a population.

Convert all continues vector to discrete vector including the nodes selection vector.

Calculate the fitness value for each particle.

Update the particle's best position (P_{best}) for all particles.

The global best position (G_{best}) is the minimum fitness value.

for each particle update the particle's velocity and position

$V_i = V_i + L_v \times Rnd\,(0, 1) \times (P_{best} - X_i) + G_v \times Rnd(0, 1) \times (G_{best} - X_i)$

$X_i = X_i + V_i$

end for

$it = it + 1$

until $it > MAX\_ITERATIONS$

Calculate $FCS\_Network$

return FCS_Network, positions

Algorithm 3: FND_GA

Input: $co\_ordinates\_nodes(x, y)$, No_FN, No_FC, No_SDN_C

Output: $cost$, $position$

$Initialize\,Population\ size$, $crossover\ probability$, $mutation\ probability$

$G_{FN_{position}} \leftarrow Random\ (coordinates\_nodes\,(x, y)\ ,\ No\_FN))$

$G_{FC_{position}} \leftarrow Random\ (coordinates\_FNs\,(x, y)\ ,\ No\_FC))$

$G_{SDN\_C\_position} \leftarrow Random\ (coordinates\_FCs\,(x, y)\ ,\ No\_SDN\_C))$

for $it = 1\ to\ MAX\_ITERATIONS$ **do**

  for $i = 1\ to\ N$ **do**

    Calculate $FCS\_Network$ with the Fitness function using $G_{FN_{position}}$, $G_{FC_{position}}$, $G_{SDN\_C\_position}$ and $Delay\_Matrices$

    Select new population using roulette wheel method

    Select individuals with crossover probability to apply two pint crossover

    Select individuals with mutation probability to apply mutation

return FCS_Network, positions

number of IoT devices, and for each device, the demand will be generated based on vCPU, memory, and bandwidth requirements. Each IoT device cluster has a coordinate (x, y) which is randomly generated in the area $100 \times 100\ km^2$. The euclidean distance between the cluster and the FN, FN and FC, FC and SDN-C is used to calculate the transmission delay. The simulation has been carried out in iFogSim simulator in Intel(R) Core (TM) i3-5005U CPU @ 2.oo GHz (4CPUs) and 4GB RAM . The process has bee tested over multiple simulations and the average value has been shown as results. For the two evolutionary algorithms, we need a population size of 100 and the number of iterations was set to 1000.
Figure 2 exhibits the effect of number of FNs on the objective function. Figure 2(a) , 2(b) shows the latency Vs the number of homogeneous and heterogeneous FNs and on varying FNs to observe the variations in the latency. The optimal number of FNs are $17 \approx 19$. From the previous simulations it has observed that, 17 number of FNs are sufficient to manage the entire network. The latency progressively decreasing on the increasing of the number of FNs. From Figure 3 (a), 3 (b), and 3 (c) it can be seen that as we are increasing the number of IoT devices , the average latency of FND_PSO algorithms is usally relatively stable in comparison to the FND_GA and FND_Random placement. It is quite essential to observe that the proposed algorithms find the appropriate number and locations of the FNs, FCs, and SDN-Cs which exploits the performance of the IoT services in the network.

V. Conclusion

In this paper, the Fog Network Design for large scale IoT applications has been reviewed. We first proposed a multi-objective mathematical model for the multi-tier fog network design. For the solution of these types of problem instances, we apply the weighted sum algorithm and two population based meta-heuristic algorithms have been proposed identified as FND_PSO and FND_GA and compare it with FND_Random approach. With regards to this, aforementioned work optimizes a set of metrics such as latency, traffic and cost to design Fog network. It is necessary to notice that the suggested algorithms finds the best possible number and position of the FNs, FCs and SDN-Cs which provide the better service in the IoT network.The simulation result shows that FND_PSO produces the optimum result. It is an important issue of managing the network when it is deployed in real world scenario. We can approach toward an systematic expertise of day to day management of these Fog nodes by switching them on/off.

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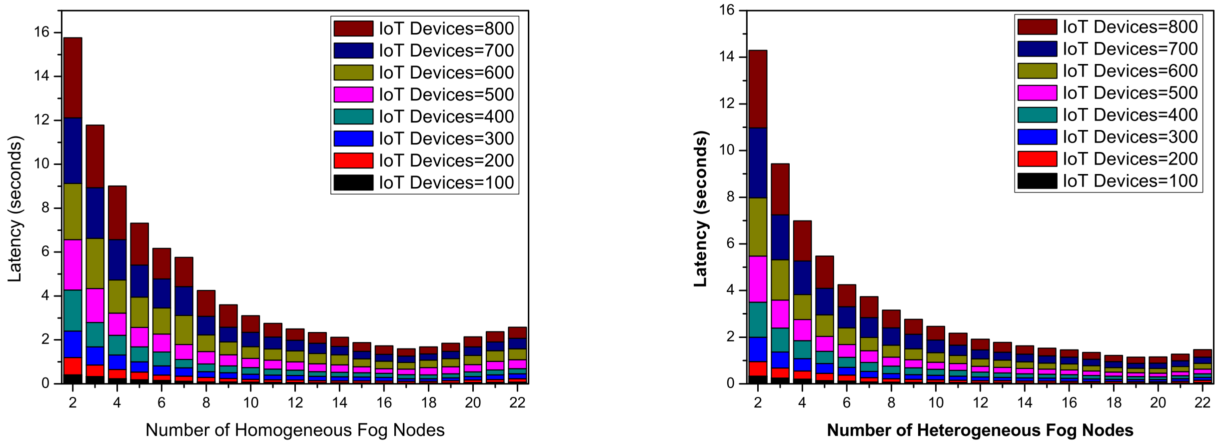
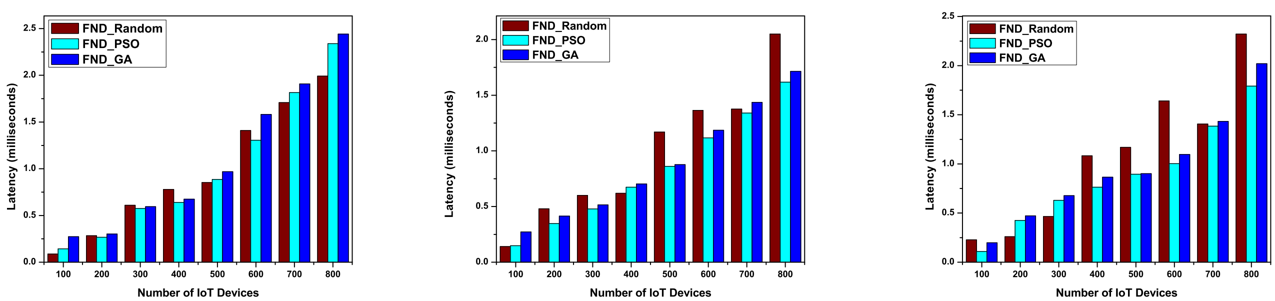


(a) Latency Vs. No. of Homoheneous FNs

(b) Latency Vs. No. of Heterogeneous FNs

Fig. 2: Different number of FNs Vs. Random deployment latency



(a) Number of FNs 17, FCs 3, SDN-C 1

(b) Number of FNs 17, FCs 3, SDN-C 2

(c) Number of FNs 17, FCs 4, SDN-C 2

Fig. 3: Average latency Vs. Number of IoT devices in different topologies

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