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Exploring Evolutionary Multi-Objective Techniques in Self-Organizing Networks

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ABSTRACT Future networks are promising to solve current issues and provide new features. Self-organizing network (SON) paradigm is one of the anticipated solutions. It involves the use of cognition concept and optimization techniques to enhance the network performance. In this paper, we propose the use of two multi-objective optimization techniques, namely, the multi-objective particle swarm optimization (MOPSO) and the multi-objective central force optimization (MOCFO) in future SON to manage system resources efficiently. Therefore, the used system design and implementation are provided. In addition, the evaluation results of the proposed two methods are compared with those obtained using the non-dominated sorting genetic algorithm (NSGA-II). Extensive simulations carried out using MATLAB package showed that MOPSO is comparable to NSGA-II and outperforms MOCFO in the network throughput. In addition, considering the needed computation time for algorithm convergence, MOPSO is faster than NSGA-II and MOCFO by 5.8 times and 9.9 times on average, respectively. Moreover, this paper provides a study on algorithm convergence rate, solution diversity, and station load.

INDEX TERMS Cognitive network, next generation network, access network selection, particle swarm optimization, central force optimization, multi-objective optimization.

I. INTRODUCTION

Nowadays information and telecommunication technologies have gained a major role in our everyday life. Our societies become more and more heavily dependent on smart devices to perform business, acquire education or get entertainment. With such importance and reliance on these technologies, people need to use these services ubiquitously (anytime and anywhere) while service providers aim to increase their profit. Thus, it is challenging to fulfill the high demand for these services with the best availability, quality, and affordability. Traditionally, researchers suggested many solutions to solve these issues such as, increasing the number of the base stations in the cell, reusing frequency for high spectrum efficiency, enhancing the backhaul network, and using Cognitive Radio (CR) approach [1]. Furthermore, others worked on clean slate solutions, like looking for architectures and frameworks to manage such complex devices and infrastructures [2]–[4].

A cost-effective solution is to utilize heterogeneous network architecture. It utilizes different and multiple Radio Access Technologies (RATs) e.g. Wi-Fi, 3G and 4G that are intersecting with each other to serve nodes as in Fig. 1. To gain this benefit, these nodes are required to have multi-network interface to use these RATs.

However, complexity and high dynamicity are the main characteristics of these networks. If the system cannot adapt intelligently to demands, a poor system performance and service blockage will be resulted. Therefore, we need to deal mainly with these vexes by handling Interference, Radio Resource Management (RRM), and Self-Organizing Networking (SON) issues.

Access Network Selection (ANS) and resource management are vital problems in the telecommunication system. The ANS problem can be defined as "The process of deciding to which proper access network a mobile shall be connected."

So, we need to decide intelligently how to select this proper network without disrupting the user experience, while preserving the strategy of the operator. Deciding the best access network does not only depend on radio

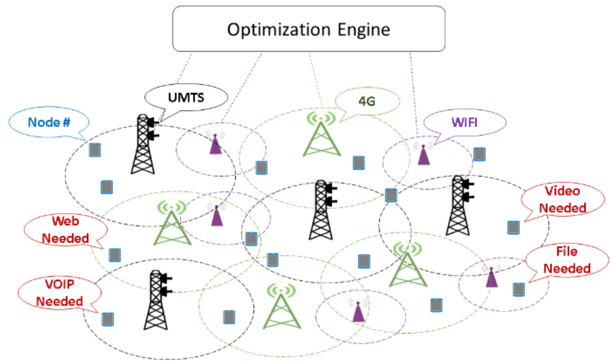

FIGURE 1. Optimization of heterogeneous network environment.

metrics, like Signal to Noise Ratio (SNR) but also on the core network measures e.g., bandwidth and load balance to prevent performance degradation due to miss planning. Consequently, in contrast to [5] we need to use multi-objective optimization to realize multiple important goals. For example, link cost, load balance and Quality of Service (QoS). They indicate the Radio Signal Strength (RSS) status, the access stations load and user experience, respectively.

Traditionally, different methods were used to solve ANS problem. Especially, multi-criteria decision-making methods, which include Simple Additive Weighting (SAW) [6], Grey Relational Analysis (GRA) [7], Analytic Hierarchy Process (AHP) [8], Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [9], and Semi-Markov Decision Process (SMDP) [10].

However, to make intelligent decisions, it is essential to have a system with three parts. First, a broad knowledge about the network status. This is realized by using knowledge module to gather data horizontally and vertically [11]. Second, self-management capabilities by applying the Cognitive Network (CN) approach. It is defined as "*A cognitive process that can perceive current network conditions, and then plan, decide and act on those conditions. The network can learn from these adaptations and use them to make future decisions, all while taking into account end-to-end goals*" [12]. The phases of the cognition cycle are "Plan", "Decide" and "Act". Third, an intelligence decision ability that could be offered by Artificial Intelligence (AI) methods such as the optimization theory. Accordingly, combining these parts with each other will enable us to optimize the network performance dynamically. In addition, recent advancement in High Performance Computing (HPC) and Machine Learning (ML) techniques will facilitate building superior networks by employing self-x framework (self-management, self-optimization, self-organizing and self-healing) [13]–[15].

This started a wave of research that utilized optimization techniques for CN problems such as [16] which used neural network as a learning scheme in the CR system while [17] used Immune Optimization Algorithm (IOA) to select the best Radio Access Network (RAN) in Joint Call Admission Control (JCAC) schemes. Besides, multi-objective genetic algorithm had been considered in [18] to optimize the QoS parameters in Mobile Ad-hoc Networks (MANETs) whereas [19] used quantum genetic algorithm as an optimization method in network selection scheme. Moreover, Q learning technique is presented in [20] to optimize the handover performance and the load among cells while [21] used a hybrid method that combines non-homogenous bio-geography based optimization (NHBBO) with the Parallel Fuzzy System (PFS) to perform RAT selection in heterogeneous wireless networks.

Recently, multi-objective Non-Dominated Sorting Genetic Algorithm (NSGA-II) has been considered to solve the ANS problem [22]. In addition, many multi-objective techniques based on particle swarm optimization (PSO) were introduced in [23] and [24]. Coello Coello and Reyes-Sierra provided a survey on multi-objective particle swarm optimization (MOPSO) with a taxonomy of approaches. The authors in [24], addressed the problem of effective spectrum allocation with the aims of maximizing the total capacity and minimizing the power consumption of a cognitive ad-hoc network. However, to the best of our knowledge, only [25] had developed a multi-objective Central Force Optimization (MOCFO) that considered the problem of combining and creating component networks in Ensemble Neural Network (ENN) which is a learning architecture that has applications in pattern recognition and medical diagnosis.

In this paper, two proposed algorithms MOPSO and MOCFO are presented in the context of the CN approach to improve the performance of the heterogeneous network. To the best of our knowledge, it is the first time where MOCFO is in implantation for a real engineering application. The results obtained using both techniques are compared to those previously considered by NSGA-II algorithm and analyzed to check their performance. Our exploration aims to find which optimization technique is superior in this kind of engineering problem.

The paper is organized as follows: In Section II, we describe the system model and formulate the problem. Multi-objective optimization techniques are presented in Section III. While in Section IV, we present simulation description and results discussion. Finally, Section V provides the conclusion.

II. SYSTEM MODEL AND PROBLEM FORMULATION

This section describes the system model used to implement the proposed multi-objective optimization techniques. The model represents a central management system that utilizes an operator-centric scheme to perform optimization globally on nodes using multi-objective algorithm. We developed the system considering the CN architecture [26] and multi-objective optimization techniques [27]. It operates by undergoing three phases: sensing phase, optimization phase, and execution phase. These phases as well as its involved

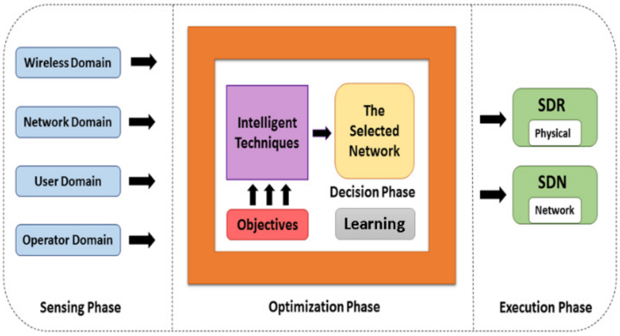

FIGURE 2. **The proposed system workflow.**

components are shown in Fig. 2. In the sensing phase, the system gets the data by sensing the environment, receiving node-transmitted data and interpreting pre-set rules. For comprehensive cognition, these data are gathered from four different domains such as Wireless, Network, User and Operator [28]. Then, in the optimization phase, the optimization engine attempts to find the best settings for the un-tuned parameters perceiving the defined goals and the ambient restrictions. This optimization engine works much like an orchestrator who maintains rhythm and harmony. By directing devices using global control channel or common middleware [22], [29], the system will be able to convey instructions to nodes or collect data from them for resources assignment or operation monitoring.

Next, the execution phase will apply the tuned setting for the parameters using Software Defined Radio (SDR) and Software Defined Network (SDN) technologies according to their operation scope as in Fig. 2. Unlike CR that uses SDR to be implemented, CN will need CR technology, SDN and AI to function properly.

This is because using algorithms solely will fail to adjust to varying conditions. Therefore, SDN architecture will ease abstracting the infrastructure for applications and network services by decoupling the network control plane and data plane, i.e. enabling the network control to become directly programmable [29] while AI is the learning process that will provide the needed self-system awareness. This design will enable us to apply end-to-end telecommunication strategy, accomplish global optimization, and realize self-optimization. Thus, a global improvement in the network performance will be obtained. In addition, this model is suggested for implementation in the Next Generation Network (NGN), e.g. 5G.

The problem is formulated as a Wireless Heterogeneous Network (WHN) as shown in Fig. 1, which consists of:

1) A number of nodes denoted as n = (1, 2, …, N) where N is the number of nodes. These nodes are Mobile Stations (MS) with multi-network interfaces.

2) A set of different overlapped RATs denoted as s = (1, 2, …, S) where S represents the number of base stations in the network. These RATs are 4G, UMTS, and WIFI.

3) A group of services denoted as y = (1, 2, …, Y) where Y denotes the available services. For instance, we have four types of services, Web, File Transfer Protocol (FTP), Voice over IP (VOIP) and Video.

Thus, for optimal operation, every node targets connectivity with the proper base station that can efficiently provide the requested service. However, we know that service providers need to assure their profit while users are looking for high quality services. Consequently, a conflict of interest will arise. So, an optimal solution should be found which should be an acceptable compromise. This conflict of interest can be represented as a multi-objective optimization problem in which three objectives, namely, link cost (F_D), load balance (F_L), and QoS (F_Q) need to be optimized simultaneously.

Multi-objective optimization problem consists of objective functions, constraints and decision parameters. Therefore, the main objective function can be described mathematically as follows:

Objective function: Min $\{F_D, F_L, F_Q\}$
subject to the following constraints [22]:

$$\sum\nolimits_{n=1}^{N} X_{ns}^{C} \le S_l \tag{1}$$

$$\sum\nolimits_{n=1}^{N} f \cdot X_{ns}^{C} \le L_s \tag{2}$$

where S_l is used to represent the allowable bandwidth per link, and considering that it cannot be higher than the station's maximum link. C stands for the channel number and X_{ns}^{C} means that if node n is connected with station s, its value will be 1 (Connected), otherwise it is 0 (Disconnected). L_s is the capacity of each station, which cannot exceed the access station load, and f is the node throughput.

The first objective is:

$$F_D = \sum\nolimits_{n=1}^{N} X_{ns}^{C} \cdot \frac{D_s}{r_s} \tag{3}$$

where F_D is the link cost of all connected nodes, Ds denotes the distance between node n and station s and r_s is the station coverage range.

The second objective is:

$$U_s = \frac{\sum_{n=1}^{N} f \cdot X_{ns}^{C}}{L_s} \tag{4}$$

$$\mu = \frac{1}{s} \sum\nolimits_{s \in S} U_s \tag{5}$$

$$F_L = \sqrt{\frac{1}{s} \sum\nolimits_{s \in S} (U_s - \mu)^2} \tag{6}$$

where F_L represents the standard deviation function for reaching load balance in the network, Us is the bandwidth utility of each station, Ls is the capacity of each station, and μ is the station average load.

The third objective is:

$$F(q) = \begin{cases} 0 & if\,(Q_{max} < q) \\ Q_{max} \frac{q - Q_{max}}{Q_{min} - Q_{max}} & if\,(Q_{min} < q \le Q_{max}) \\ Q_{max} & if\,(q \le Q_{min}) \end{cases} \tag{7}$$

TABLE 1. The thresholds of service requirements.

Name	Maximum Throughput (DL) (kbps) Q_{max}	Minimum Throughput (DL) (kbps) Q_{min}	Maximum Throughput (UL) (kbps) Q_{max}	Minimum Throughput (UL) (kbps) Q_{min}
Web	128	64	64	32
FTP	1000	0	100	0
Video	64	64	64	64
VOIP	12.2	12.2	12.2	12.2

$$F(q) = F(f.X_{ns}^{C}) \tag{8}$$

$$F_Q = \sum_{n=1}^{N} F(q) \tag{9}$$

where F_Q represents the penalty of QoS for all the nodes in the network.

Noting that each type of service has a different throughput threshold (The rate of successful received data packets per second to the receiver) [30]. When a node uses a downlink (DL) or uplink (UP) service, the proportional penalty is generated from the value of the benchmark q in Eq. (8). The corresponding penalty for each service shown in Table 1 and denoted by Q_{max} and Q_{min} in Eq. (7). Hence, we need to select the proper QoS for every service. The threshold-based function in Eq. (9) is used for giving a penalty in proportion to different service requirements and to avoid providing insufficient network resources for nodes as shown in Table 1. This penalty function works as following:

1) For high throughput, no penalty will be applied.
2) For high throughput, but within the maximum and minimum threshold, a moderate penalty will be applied.
3) For low throughput, the maximum penalty will be applied.

Thus, for better QoS, we aim to find smaller value which reflects high throughput for all nodes.

As for the decision parameters, we used link cost and bandwidth to tune the system performance. However, this multi-objective optimization problem is very challenging in the representation of these decision parameters. For example, the service bandwidth parameter gets only one value from three possible ones (discrete); Bandwidth (BW) = [64, 96, 128] (Kbps) while the link cost parameter equals a real value in the range [0-1] according to the base station location, node location and the station coverage range. Nevertheless, this value identifies the available base stations for every node, which is different from node to another, making the selection process – sometimes – hard. To tackle this problem, we used the "rounding off" technique for easiness [31].

On the other hand, the following metrics are used for evaluation:

1- The system throughput:

$$\mathrm{F} = \sum_{s=1}^{S} L_s \tag{10}$$

2- The computation time for complete iterations:

$$\mathrm{T_{comp}} = \sum_{Itr=1}^{ITR\_MAX} T_{ITR} \tag{11}$$

Where $\mathrm{T_{ITR}}$ is the computation time per iteration and ITR_MAX is the number of complete iterations.

3- The computation time for convergence iterations:

$$\mathrm{T_{conv}} = \sum_{Itr=1}^{ITR\_CONV} T_{ITR} \tag{12}$$

where ITR_CONV is the number of iterations for convergence.

III. OPTIMIZATION PROBLEM

An optimization problem is the problem of finding the best solution from all feasible solutions. This solution should give the values of all the objectives acceptable to our aim.

A. EVOLUTIONARY MULTI-OBJECTIVE TECHNIQUES

Multi-objective optimization techniques have been considered to solve many engineering problems. It enables us to consider many facets for optimization simultaneously. Hence, it will effectively satisfy the user, the service provider, and network needs. Many methods were considered to solve Multi-objective Optimization (MOO) problems. For example, Weighted Sum, ε-Constraint, Goal Programming and Heuristic Methods. We used here the Heuristic methods. Its advantage has two folds. First, it works as a black box, so there is no need for special function. Second, it has the ability to find all the best solutions simultaneously to use. Therefore, objective weight is not required.

In general, PSO and Central force optimization (CFO) techniques can be classified under Evolutionary Algorithms (EA) scheme because these algorithms apply the concept of evolution. This concept symbolizes the passing of time as imitation of nature. It works by employing iterations in the algorithm to improve the solution quality until the stopping criteria is met. Besides, EA is commonly used for generating Pareto optimal solutions which is a set of solutions, where no solution is better than the other in all the objectives required.

Recently, PSO and CFO are well-known alternatives for global optimization based on a nature-inspired heuristic [32], [33]. PSO showed to have good performance, low computational complexity, few configuration parameters and give good results. On the other hand, CFO has many merits such as the simple form of mathematics, the ease of implementation, and the high rate of convergence [33]. However, CFO has a higher computational complexity but it gives better result [34]. As tested before on several benchmarks, PSO and CFO have completely different mechanisms, where PSO is better for single optimum functions while CFO is better for multi-optimum functions [34]. However, it is necessary to point out that, there is no optimizer that can be optimal for all possible problems [35]. Therefore, both algorithms (MOPSO and MOCFO) are studied to find the most proper technique for the problem of wireless access selection, which is still under investigation and the results are compared to the well-known NSGA-II algorithm.

B. THE PROPOSED MOPSO MODEL

The popular PSO algorithm mimics the movements of a flock of birds to find food [32]. It is a kind of swarm intelligence where each particle's location in the search space represents a possible solution for the optimization problem. The basic algorithm simply operates by using two equations: one for velocity and the other for position. The algorithm reaches the solution by continuously changing the particle position (possible solution), and then it uses the velocity equation.

After that, it selects the best particle (global) in every iteration until the algorithm's maximum iteration is reached.

We adapted a MOPSO version from [36] and added some aspects for fair comparison and performance improvement such as: Time Variant Acceleration Coefficients (TVAC) in Eqs. (14-16), mutation, and different leader selection mechanism. Original MOPSO selects the leader particle randomly from certain grid. Here, we select the leader particle based on crowding distance and the best particle. We found that modified MOPSO is better than original MOPSO by 4.8% in throughput [37]. For detailed steps, the following pseudo code explains the modified MOPSO algorithm and also a flow chart in Fig. 3.

C. THE PROPOSED MOCFO MODEL

CFO algorithm is a new optimization technique based on the metaphor of gravitational kinematics which is introduced in [33]. It represents "probes" that "fly" through the decision space by analogy to masses moving under the effect of gravity. We adapted the standard CFO algorithm by adding multi-objective capabilities, mutation and crowding distance parameter for ranking. For multi-objective, it should be noted that one of the most important points is how to select the global best because it balances between the convergence and diversity. Exploring the strategies to find the best one, we found that in a fully connected swarm, various strategies have been proposed such as random, grid, sigma, nearest. Thus, we employed the grid strategy for its low computational cost, middle optimality and weak determinism (the probability to change global best in the next iterations) [38]. It is used to distribute uniformly the largest possible amount of hyper-cubes. These hyper-cubes are formed by dividing the objective function space into regions. Such hyper-cubes has as many components as objective functions. Each hyper-cube can be interpreted as a geographical region that contains a number of solutions [36].

In addition, a main difference between MOPSO and MOCFO is that MOCFO's acceleration equation depends on the number of objectives. Consequently, in case of three objectives -our case- we will have three acceleration values, i.e., each acceleration value will be sent to a different

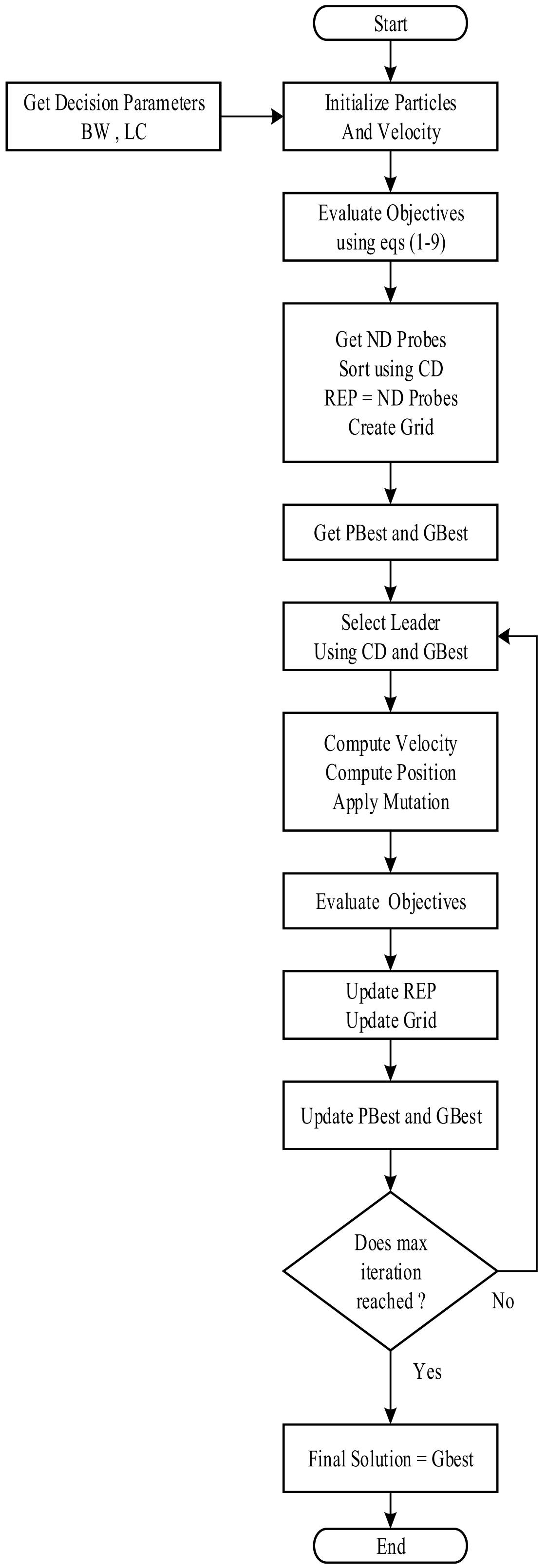

FIGURE 3. MOPSO algorithm flow chart.

group to calculate its objective functions. Unlike method [25] to implement multi-objective CFO, the proposed MOCFO assumes that the three groups Y1, Y2, and Y3 are targeted to

Pseudo Code 1: MOPSO Algorithm

1) Initialize the population of the PARTICLES:
   a) FOR i = 0 TO nPOP, where nPOP = number of particles
   b) Initialize PARTICLES [i].
2) Initialize the velocity of each particle:
   a) FOR i = 0 TO nPOP
   b) Velocity [i] = 0
3) Evaluate Objectives for PARTICLES using Eqs. (1-9).
4) Get best fitness GBest.
5) Initialize respiratory REP.
6) Get non-dominated solutions.
7) Sort solutions using crowding distance parameter.
8) Store sorted non-dominated solutions in the repository REP.
9) Create grid for the search space and locate the particles within it.
10) Initialize the memory of each particle
    a) FOR i TO nPOP
    b) PBest [i] = PARTICLES[i]
11) For Itr = 1 TO ITR_MAX where ITR_MAX = Number of Iterations
    a) If Itr = 1 REP[h] = any else REP[h] = PBest[i] END
    b) Calculate velocity of each particle using the equation:

$$\begin{aligned} Velocity\,[i] = {} & w * Velocity\,[i] + C1_{Itr} \\ & * (PBest\,[i] - PARTICLES\,[i]) \\ & + C2_{Itr} * (REP\,[h] - PARTICLES\,[i]) \end{aligned} \tag{13}$$

Where h index is the grid selection criteria, w is the inertia weight that dynamically takes a value from [0.4 – 0.9], $C1$ and $C2$ are exploitation and exploration parameters that take values in the range [0.5-2.5] according to the following:

$$w = w_{max} - \left(\frac{w_{max} - w_{min}}{ITR_{max}}\right) * Itr \tag{14}$$

$$C1_{Itr} = c1_{max}\left(\frac{c1_{max} - c1_{min}}{ITR_{max}}\right) * Itr \tag{15}$$

$$C2_{Itr} = c2_{max} + \left(\frac{c2_{max} - c2_{min}}{ITR_{max}}\right) * Itr \tag{16}$$

12) Calculate the new positions of the particles using the equation:

$$PARTICLES[i] = PARTICLES[i] + Velocity[i] \tag{17}$$

13) Preserve the particles within the search space in case they go beyond their boundaries.
14) Apply mutation to PARTICLES [i].
15) Calculate the objectives for PARTICLES [i] using Eqs. (1-9):
16) Update the repository REP and the geographical representation of the particles.
17) Get and sort the solutions using crowding distance.
18) Select best objective and check if the current position of the particle is better than the position contained in its memory; the particle's position is updated using the equation:

$$PBest[i] = PARTICLES[i] \tag{18}$$

19) END of Itr.

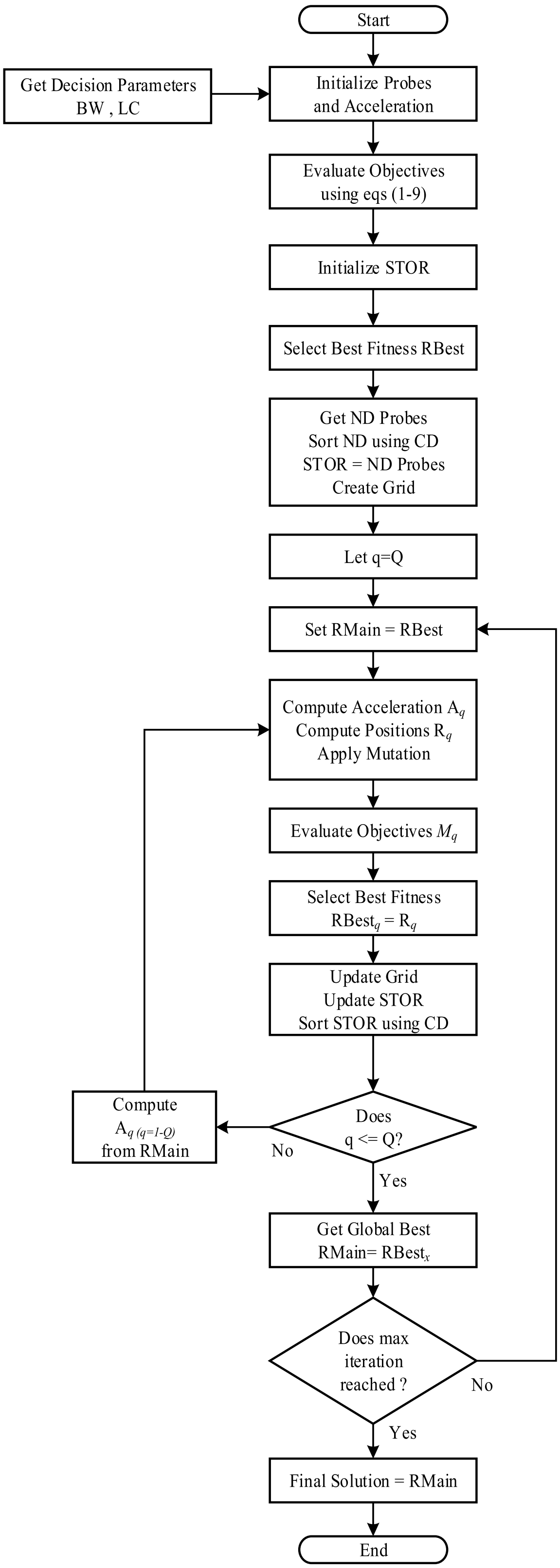

FIGURE 4. MOCFO algorithm flow chart.

optimize simultaneously three-objective functions link cost, load balance, and QoS.

For every group, its objective functions are calculated and denoted as $M1$, $M2$ and $M3$. Then, the group with the best values, utilizing the star migration topology, is selected to influence others [23]. The proposed MOCFO algorithm is explained in the following Pseudocode and demonstrated by a flow chart in Fig. 4.

Pseudo Code 2: MOCFO Algorithm

1) Initialize the probes:
   a) FOR $p = 0$ TO NP, where NP = number of probes.
   b) Initialize R_{Main} $[p]$, represent main probes.
   c) Initialize $R_q[p] = R_{Main}[p]$, represent group probes where q is the group number according to number of objectives Q. (Number of groups = Number of objectives)
2) Initialize the acceleration:
   a) FOR $p = 0$ TO NP
   b) Initialize $A_{Main}[p] = 0$, represent main acceleration.
   c) Initialize $A_q[p] = A_{Main}[p]$, represent group acceleration.
3) Evaluate objectives for R_{Main} and R_q according to the Eqs. (1-9).
4) Get best fitness R_{Best}.
5) Initialize respiratory STOR.
6) Get non-dominated solutions.
7) Sort non-dominated solutions using crowding distance parameter.
8) Store sorted non-dominated solutions in the repository STOR.
9) Create grid for the search space and locate the probes within it.
10) Initialize the memory of each probe:
    a) FOR p TO NP
    b) $RBest_q[p] = R_q[p]$
11) FOR j = 1 TO J where J = Number of Iterations.
    a) For every group R_t.
    b) Select leader:

$$\text{IF } j = 1 \text{ REP}[p] = \text{any ELSE REP[p]} = \text{RBest[p]END}$$

    c) Calculate the acceleration of each probe using the equation:

$$A^p_{j-1,q} = G_0 \sum_{\substack{k=1 \\ k \neq p}}^{N_p} U\left(M^k_{j-1,q} - M^p_{j-1,q}\right) \times (M^k_{j-1,q} - M^p_{j-1,q})^{\alpha} \frac{(R^k_{j-1,q} - R^p_{j-1,q})}{\left\| R^k_{j-1,q} - R^p_{j-1,q} \right\|^{\beta}} \tag{19}$$

    where U is the Unit Step function:

$$U(z) = \begin{cases} 1, & z \geq 0 \\ 0, & Otherwise \end{cases} \tag{20}$$

    G_0 is CFO's gravitational constant = 1, p and k are two counters for Np, α and β are two constant = 2, and M is the Mass and represents objective functions defined in Eqs. (1-9).
    d) Calculate the new positions of the probes using the equation:

$$R^p_{j,q} = R^p_{j-1,q} + \frac{1}{2} A^p_{j-1,q} \Delta t^2, \quad j \geq 1 \tag{21}$$

    where t is the time and equal 1.
    e) Preserve the probes within the search space in case they go beyond their boundaries.
    f) Apply mutation to $R_q[p]$.
    g) Calculate the objectives for each probes in R_q $[p]$ using previous Eqs. (1-9):
    h) Update the repository STOR and the geographical representation of the probes.
    i) Determine and sort the solutions using crowding distance.
    j) Select best objective RBest and check if the current position of the probe is better than the position contained in its memory; the probe's position is updated using the equation:
    k) Assign best objective of the groups as $R_{Main} = RBest_x$, where x is the number of the group with best objective.

$$RBest_q[\text{p}] = R_q[\text{p}] \tag{22}$$

12) End FOR.
13) Return the final solution.

IV. SIMULATION MODEL AND RESULT DISCUSSION

We developed a system-level simulation based on the work of [22] and [39] using MATLAB 8.1. Our case scenario simulates an overlapping WHN as shown in Fig. 5 with simulation parameter settings as in Table 2. The simulation program works as follows: First, a certain number of each base station type - for instance WIFI, UMTS and 4G - is randomly distributed in a given area. Then, a number of nodes are distributed randomly within the same area. Stations ID and nodes ID are illustrated by numbers as shown in Fig. 5.

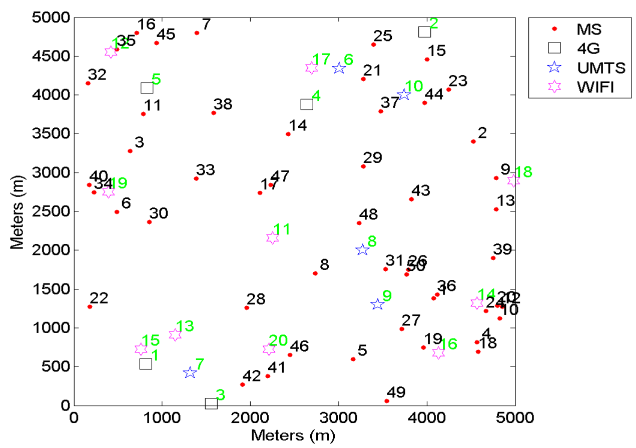

FIGURE 5. Simulation topology for a wireless heterogeneous network.

Next, every node has assigned only one service from available services. For fairness, these services are distributed uniformly among nodes. The optimization algorithm tries to find the best available base station for each node while achieving global objectives, like high throughput. This is done by evaluating many solutions per iteration and then selecting the best solution until it reaches the end of iterations.

For better understanding, we can visually represent the solutions as in Fig. 6. This format consists of a number of nodes in each row which is known as a population. Each node

TABLE 2. Simulation scenario setting.

Name	Value
Area size	5kmx5km
Stations Location	Fixed Distribution
Stations Type	4G – UMTS – WLAN
Number of Stations	20 ; (4G/UMTS=5; WIFI=10)
Station's Range Radius	4G / UMTS = 2.5 Km; WIFI = 500 m
Base Station Capacity	4G / WIFI =100MB; UMTS= 2MB
Allowed BW per link	4G / WIFI = 5 Mb/s; UMTS= 0.2 Mb/s
Nodes Type	Multi-Network Interface MS
Number of Nodes	[50 - 300]
Service Distribution Model	Uniform

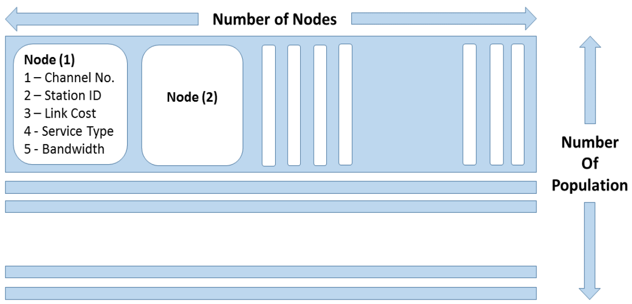

FIGURE 6. The population format for proposed algorithms.

has some parameters: channel number, station ID, link cost, service type and bandwidth.

The considered setting for the optimization algorithm itself is given in Table 3. For fair comparison between different algorithms, the same number of evaluation (10,000) has been considered for all techniques. System performance has been evaluated by calculating the overall system throughput and the computation time.

TABLE 3. The proposed algorithms setting.

Name	NSGA-II	MOPSO	MOCFO
Population Size	100	100	100
Repository Size	100	100	100
Iteration Number	100	100	100
Number of Grids	-	30	30
Mutation	0.1	0.1	0.1
Crossover Rate	0.5	-	-

Fig. 7 (a - f) shows the network throughput versus iterations to assess the convergence rate for different number of nodes (50, 100, 150, 200, 250, and 300) considering MOPSO, MOCFO, and NSGA-II techniques. The figures show that, MOCFO can converge faster than MOPSO and NSGA-II algorithms by 16% and 34%, respectively. Also, as the number of nodes increases, MOCFO convergence improves compared to other algorithms.

In Fig. 8, we investigate the solutions diversity as an important metric for EAs. Generally, low diversity is one of the main reasons for premature convergence (stagnation) while high diversity allows for better solutions. Fig. 8 (a-b) shows the population in NSGA-II algorithm at iteration number 50 and 100 respectively. We observed that, chromosomes of NSGA-II performed well and had a good convergence and diversity. Similarly, the particles of MOPSO algorithm are shown in Fig. 8 (c-d). It is found that MOPSO can get the best solutions with low diversity. The reason behind is that the algorithm-methodology allows one or some of the particles to exist near the optimum solution in the search space.

Fig. 8 (e-f) demonstrates the probes of the MOCFO algorithm at iteration number 50 and 100 respectively. We note that the diversity is retrogressed which led to producing a lower number of solutions.

Fig. 9 (a) shows the average overall network throughput versus the number of nodes for NSGA-II, MOPSO, Original MOPSO, MOCFO and original IP Multimedia System (IMS) system over 100 independent runs. Generally, any of the optimization algorithms outperforms the original IMS system in the network throughput which reflects the importance of considering the optimization technique in this application. MOPSO performs better than Original MOPSO. As a comparison between the obtained results using different techniques, it is found that MOPSO has outperformed the network throughput by 3% than NSGA-II and by 26% than MOCFO for different number of nodes (those less than or equal to 200 nodes).

While for the number of nodes more than 200, the NSGA-II is found to be better than MOPSO by 3% and by 28% than MOCFO. Fundamentally, it is important to know the time needed to get a solution which is represented by computation time. The lower this number is, the better. Every algorithm has its run-time complexity. For the basic MOO program, the needed run times is O (GMN2) where G is the number of generations, M is the number of objectives and N is the population size. This is improved by using the fast non-dominated sorting method to a run-time complexity of O (GN log M-1N) [30]. However, the needed time to calculate one iteration is different from algorithm to another.

Therefore, Fig. 9 (b) shows the percentage of full computation time (100 iterations) versus the number of nodes for MOPSO, NSGA-II and MOCFO. This percentage is normalized on MOCFO time. Mainly, a linear growth of the computation time is observed as the number of nodes increases. On average, MOPSO is found to be faster than NSGA-II and MOCFO by 4.02 times and 22 times, respectively. However, it should be noted that MOCFO is converged faster than other algorithms as described before.

Additionally, Fig. 9 (c) shows the percentage of convergence computation time versus different number of nodes for MOPSO, NSGA-II and MOCFO. We can get this percentage by normalizing on MOCFO time. The figure declares that, MOPSO is found to be faster than NSGA-II and MOCFO by 6.22 times and 9.88 times, respectively for the computation time of the algorithm convergence. Hence, the time saving is more if we used this feature as a stopping criterion.

Fig. 10 (a-c) shows the load percentage of NSGA-II, MOPSO and MOCFO for different RAT. This percentage is calculated by normalizing each RAT Load by the total

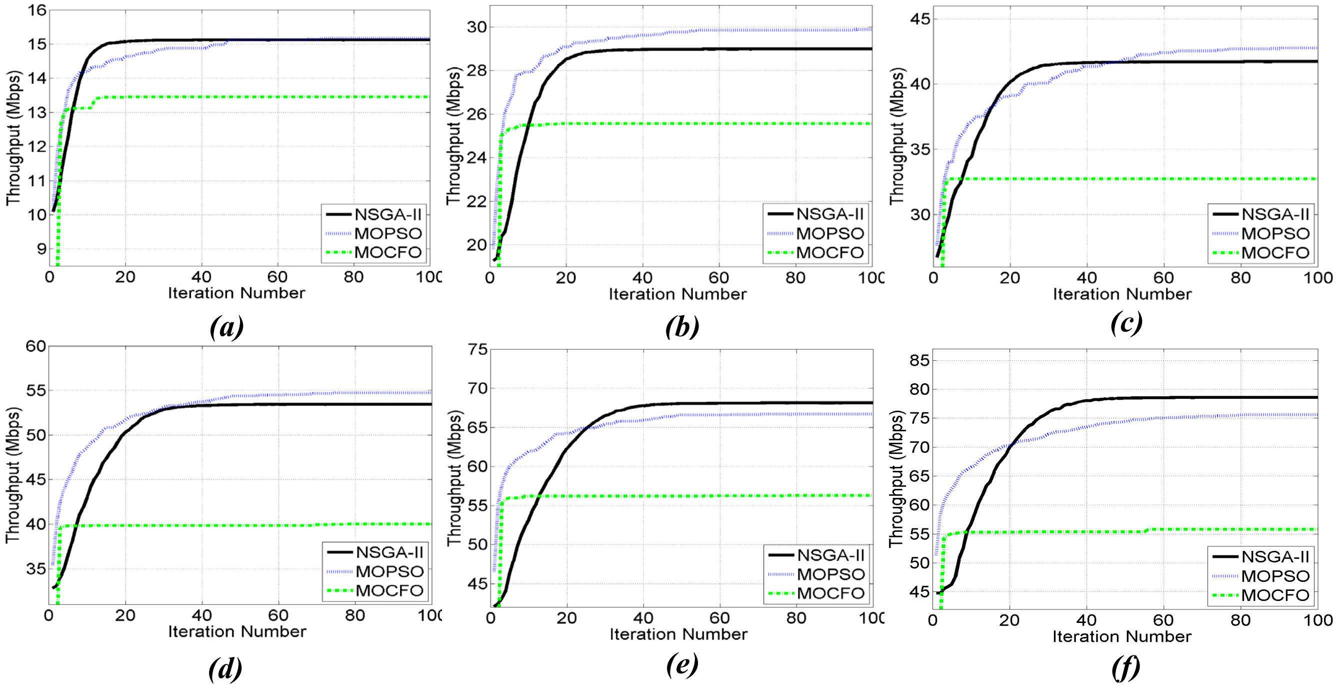

FIGURE 7. Convergence rate for throughput. (a), (b), (c), (d), (e) and (f) show the network throughput vs. iterations number for 50, 100, 150, 200, 250 and 300 nodes, respectively.

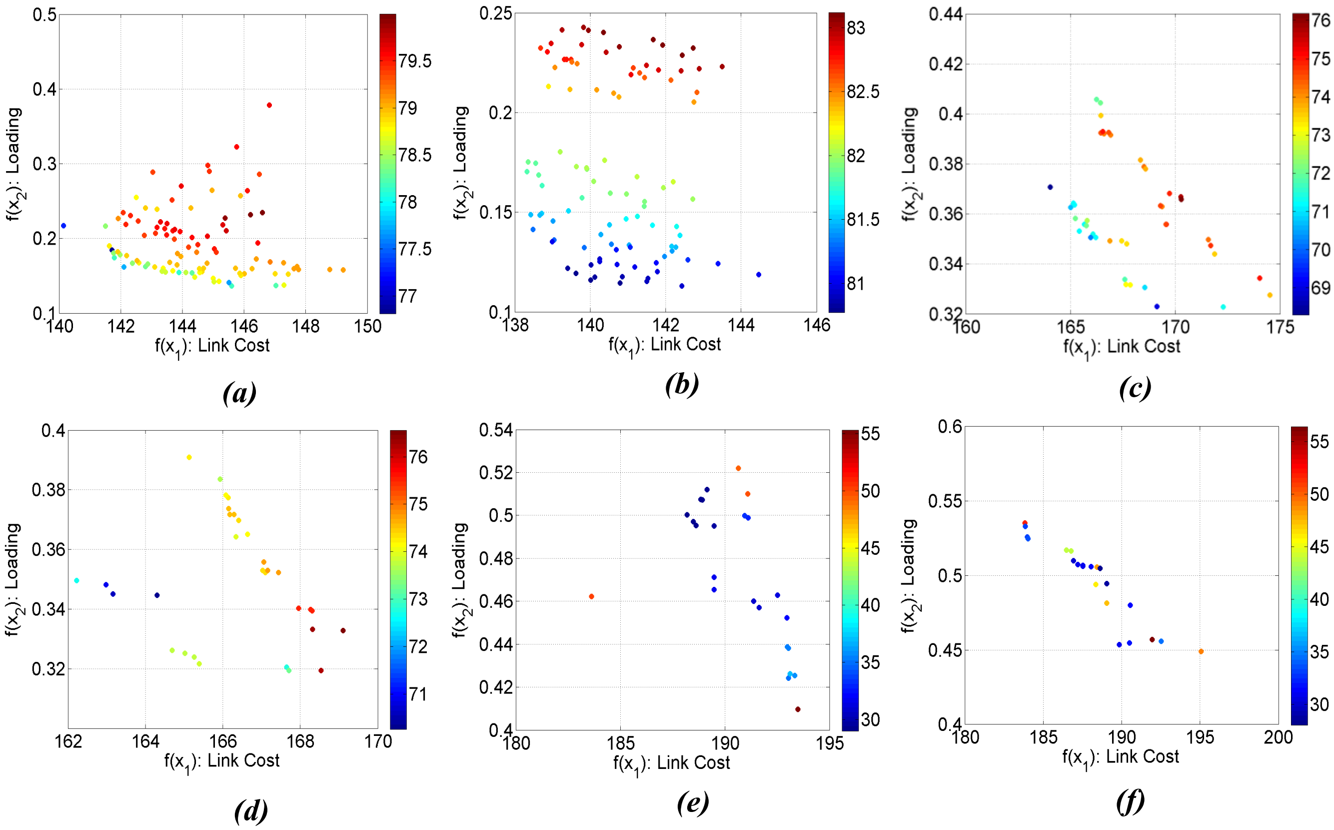

FIGURE 8. Solution diversity for NSGA-II, MOPSO, and MOCFO algorithms. (a) NSGA-II cromosomes at iteration = 50, (b) NSGA-II cromosomes at iteration = 100, (c) MOPSO populations at iteration = 50, (d) MOPSO populations at iteration = 100, (e) MOCFO probes at iteration = 50, (f) MOCFO probes at iterstion = 100.

network throughout for its algorithm. It could be concluded that due to algorithms operation behavior, NSGA-II algorithm tends to select 4G network, WIFI network and then UMTS network while MOPSO and MOCFO incline to choose 4G stations, UMTS stations and then WIFI stations. Generally, NSGA-II has many nodes connected to 4G RAT

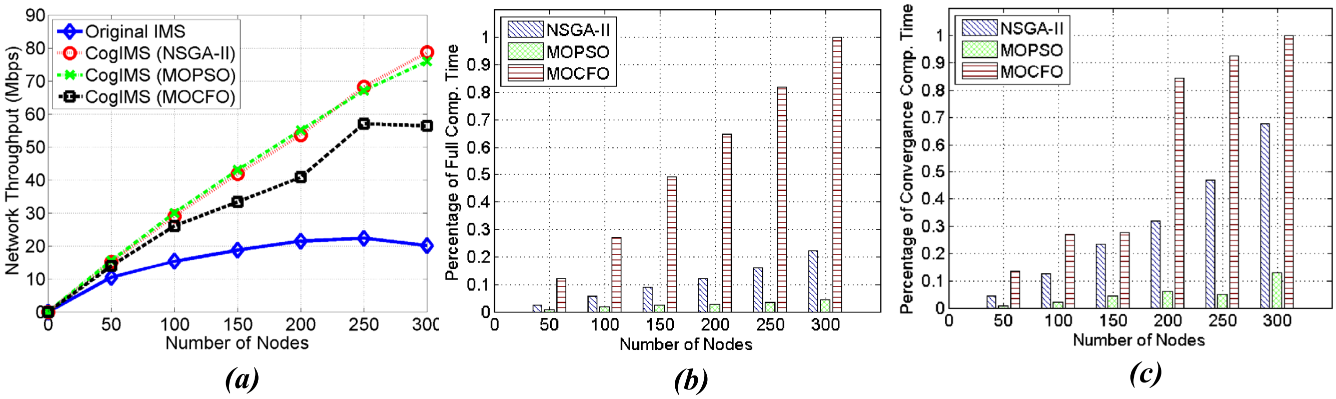

FIGURE 9. Performance metric vs. number of nodes. (a) Overall network throughput vs. number of nodes. (b) Percentage of full computation time vs. number of nodes. (c) Percentage of convergence computation time vs. number of nodes.

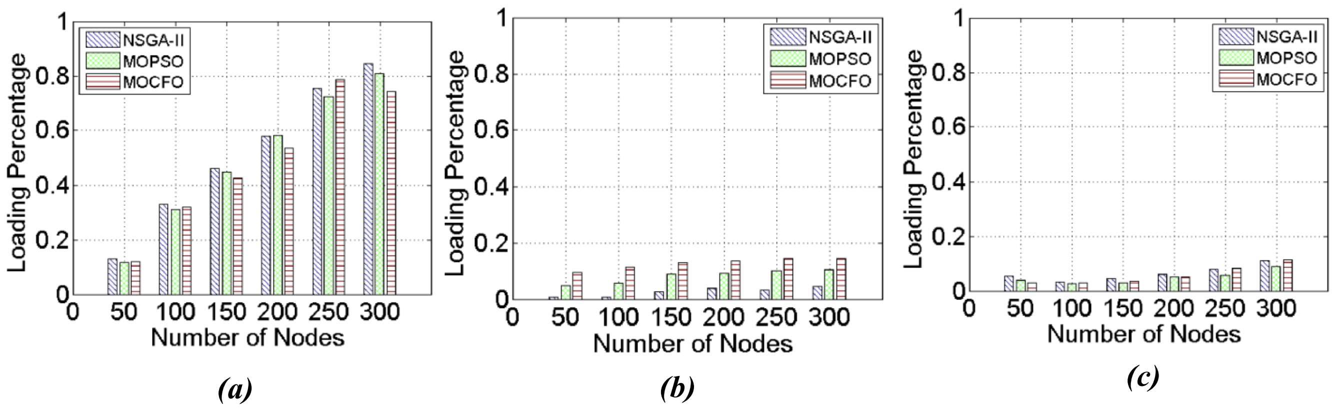

FIGURE 10. Loading percentage of different RATs for MOPSO, NSGA-II, and MOCFO. (a) 4G RAT, (b) UMTS RAT, (c) WIFI RAT.

than other algorithms while MOCFO major nodes connected to UMTS RAT. This helps in network design and planning.

V. CONCLUSION

In this paper, a comparative study has been carried out between NSGA-II and the proposed techniques (MOCFO and MOPSO) in the context of the CN approach to solve the ANS problem.

Moreover, we investigated different metric such as convergence rate, solutions diversity, overall network throughput, computation time, and loading of access stations for different RATs. We have considered a simultaneous optimization of three objectives, namely link cost, quality of service and load balance with the aim to minimizing these objectives.

The obtained results revealed that, modified MOPSO is better than NSGA-II and MOCFO in terms of computational time. However, in terms of throughput, the modified MOPSO and NSGA-II are comparable and they are far better than MOCFO. Therefore, given the slight enhancement NSGA-II provide for number of nodes over 200 versus the huge time needed to compute it. It is apparent that it is not worth it. So, we can say that the modified MOPSO algorithm outperformed the well-known NSGA-II algorithm and the proposed MOCFO in terms of computational time and network performance. On the other hand, MOCFO can converge faster than MOPSO and NSGA-II algorithms. Thus, the proposed algorithm can enhance the global network performance while realizing the best experience for users and telecommunication strategy for service provider.

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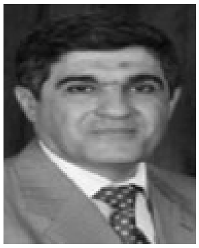

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