2. Related work

2.1. Single objective optimization in WMN

Several routing protocols are used in WMN but most of the protocols consider only one objective either throughput or delay or hop count or packet loss or energy. Sun et al. [10] proposed on demand code aware routing scheme (OCAR) for WMN. This scheme detects a route with more network coding opportunities along the entire route rather than the two-hop regions. By using Coding Aware and Interference avoid routing metric (R_{CAIA}), OCAR handle both intra and inter flow interferences. R_{CAIA} of link l is given by

$$R_{CAIA} = \frac{1}{I_l} R_{CAETT_{nl}}, \tag{1}$$

where R_{CAETT} refers to coding aware expected transmission time. When there is no interference I_l is considered as 1 and therefore R_{CAIA} becomes equal to R_{CAETT}. The coding-aware and interference avoid routing metric of flow f_n's path L is given by

$$R_{CAIA} = \sum_{l \in L} R_{CAIA_{nl}}. \tag{2}$$

Baumann et al. [11] proposed the field based anycast routing protocol (HEAT). Here, the mesh nodes are represented as the temperature values and the gateway act as the heat sources of a temperature field. Based on the HEAT beacon messages, every mesh node calculates its temperature using the field calculation function algorithm. In this algorithm, for every node sort (ascending) its neighbor based on their temperature value and store into some array. For each node j, the value $t_j + 1$ is calculated as

$$t_j + 1 = t_j + (a_j - t_j) * k, \tag{3}$$

where a_j-temperature of currently consider neighbor, t_j-accumulated temperature, k-conductivity parameter ($k = \frac{1}{4}$).

The value of $t_j + 1$ is repeated, until the temperature of the next neighbor is less than the accumulated temperature. After the temperature calculation, the packets are routed from the mesh node to the gateway on hop-by-hop basis. A packet is always forwarded to the neighbor with the highest temperature value. An interference aware analytical routing metric is proposed by Alotaibi et al. [12]. The integer programming model is used to maximize the successfully transmitted traffic of all sources to destination pairs. This model achieved a performance improvement in throughput by 52% compared to other routing metrics.

Hou et al. [13] described the maximum available bandwidth path using a proactive hop by hop routing protocol. By using the left-isotonic path weight, the source can immediately determine the infeasible connection requests as well as the consistency and loop-freeness requirements. Simple opportunistic adaptive routing protocol (SOAR) was proposed by Rozner et al. [14]. SOAR effectively realizes opportunistic forwarding by judiciously selecting forwarding nodes and employing priority-based timers. The Adaptive rate control is used to determine an appropriate sending rate, according to current network conditions and recover the lost packets using local feedback method.

2.2. Multiobjective optimization

A complete discussion of MOEAs is presented in [4]. Zhou et al. [15] gave a detailed survey of numerous multiobjective evolutionary algorithm and emphasizes the recent developments together with algorithmic rule frameworks, selection strategies, offspring reproduction schemes and other related issues.

Abel Garcia-Najera and Bullinaria [16] introduced an improved multiobjective evolutionary algorithm (IMOEA) for vehicle routing problem. This algorithm simultaneously minimizes three objectives, namely number of routes, travel distance and delivery time. It is observed that IMOEA performs better than NSGA-II for both the bi-objective and tri-objective cases. Jiang et al. [17] proposed NSGA-II for designing a fiber Bragg grating (FBG) sensor network. The objectives considered are bandwidth and the overlap degree of spectra. This approach significantly saves the bandwidth and improves the multiplexing capability for Wavelength Division Multiplexing (WDM) Fiber Bragg Grating (FBG) sensor network. A coverage control scheme for WSN based on improved NSGA-II was proposed by Jia et al. [18,19]. The energy aware routing protocol by using NSGA-II for the Wireless Multimedia Sensor Network was developed by EkbataniFard and Monsefi [20]. This protocol outperforms the network performance by optimizing the multiple QoS parameters.

The multiobjective scheduling algorithm using R-NSGA-II was proposed by Garg and Singh [21]. The objectives considered are execution time and total cost. R-NSGA-II provides an optimal scheduling solution and it satisfies the quality of service constraints. R-NSGA-II algorithm uses the preferred distance instead of crowding distance which is used in NSGA-II. The preference distance represents the closeness of the solution for the user specified region. This algorithm generates the solution in the region of user interest rather than finding out which are not of user interest.

2.2.1. Multiobjective optimization in WMN

Camelo et al. [22] designed a multiobjective routing in WMN using NSGA-II by considering three objectives: minimizing the packet loss, end-to-end delay and power consumption. NSGA-II finds the multiple paths which guarantee QoS requirements and also support the multimedia data transmission. The multiobjective approach for joint routing and scheduling problem is described by Gomes and Huiban [23]. To satisfy the multi-access interferences the authors considered two objectives, balancing the load in the routers and communication time which corresponds to the time required to route all the router demands. The authors used column generation method to improve efficiency for computing the solutions.

Xhafa et al. [24] presented the placement of mesh router nodes in WMN using simulated annealing (SA) approach. This optimization model uses two maximization objectives, namely network connectivity and user coverage. A number of client mesh nodes are priori distributed in a grid area arranged in small cells and a number of mesh router nodes are to be deployed in the area. The simulation results confirmed that, SA approach is suitable for the placement of mesh router nodes in WMNs for different topology. A particle swarm optimization approach for optimizing dynamic router node placement of WMN is proposed by Lin [25]. The mathematical formulation of the problem is used to identify the dynamic placement of mesh routers in a geographical area while maximizing the two objectives: network connectivity and client coverage. The simulation results show that the quality of the PSO approach through sensitivity analysis as well as the adaptability to the topology changes at different times. Benyamina et al. [26] proposed a three multiobjective models of WMN planning problem using a hybrid combination of multiobjective particle swarm optimization and genetic algorithm. This model simultaneously optimizes the network deployment cost and network throughput objectives. Load-balanced model generates a broader set of non-dominated solutions and provides better throughput than the other two models.

Mostly WMN routing problem has been considered as a single objective problem, but it can have more than one objective. A number of assorted approaches have been proposed for improving WMN routing, which includes the utilization of heuristics, a single metric, a composite metric, multiple metrics and multidimensional metrics [7–9,34]. In a very few papers, it has been treated as a multiobjective problem. To evaluate the distribution of the individuals, the crowding distance is used in NSGA-II. Moreover, the crowding distance does not consider the uniformity of the individual distributions in each non-dominated front and in some conditions, it may destroy the uniformity. To improve the uniformity of the individual distributions, a DCD approach is proposed in this paper. The objective of this paper is to solve the multiobjective routing problem using MNSGA-II algorithm by means of incorporating the concept of DCD in the original NSGA-II algorithm. We consider both expected transmission count and transmission delay simultaneously to determine the optimal routing for WMN. Analytic hierarchy process (AHP) is adopted to rank the Pareto-optimal solutions, to determine the best route between a given source and destination.

Contributions that are made in this paper can be summarized in the following way:

1. We formulate the problem as multiobjective shortest path routing for the minimization of transmission delay and expected transmission count.
2. We use modified elitist non-dominated sorting algorithm (MNSGA-II) to find the Pareto optimal solutions and then employ a decision making process, i.e. analytic hierarchy process (AHP) to choose the best compromise solution.
3. The performance of the proposed algorithm is analyzed through the simulation studies.

3. Problem formulation

Wireless mesh network can be represented as an undirected graph $G=(V, E)$ where V is the set of nodes consisting of both mesh client and mesh routers and E is the set of edges representing wireless links between the nodes. A path from node V_i to node V_j is the sequence of nodes from V in which no node appears more than once. The routing problem is to determine a path between the source and destination nodes with minimum transmission delay and minimum expected transmission count.

3.1. Decision variable

The binary decision variable (X_{ij}) will tell us whether a particular link $(i, j) \in E$ is considered in a routing path or not. The variable is defined as follows:

$$X_{ij} = \begin{cases} 1 & \text{if the link } (i,j) \text{ is included in the path.} \\ 0 & \text{if the link } (i,j) \text{ is not included in the path.} \end{cases}$$

3.2. Objective functions

3.2.1. Transmission delay

This objective function is to minimize the transmission delay while transferring the packets from source to destination. The smoothed transmission delay of a node A is given by

$$STD_n, A = \sum \alpha(1-\alpha)^{n-i} D_{i,A}, \tag{4}$$

where n is the number of received probes, α is a smoothing factor and D is the current measured delay for node.

The minimization function model has been adopted from Weverton et al. [27]. The route with least sum of transmission delays for all hops is chosen as the best path.

The objective function for the minimum transmission delay can be expressed as follows

$$f_1 = \min \sum_{(i,j)\in E} D_{i,j} X_{i,j}. \tag{5}$$

3.2.2. Expected transmission count (ETX)

This objective is to choose the routes with a minimum expected number of transmissions. The ETX of a link is the number of data transmissions required to send a packet over that link, including retransmissions [28]. Consequently, the selected routes have high throughput. The ETX metric for a path p consisting of links $v_1, v_2, \ldots, v_n$ with the forward delivery ratio of fd_{v_i} and reverse delivery ratio of rd_{v_i} for link v_i is computed as

$$etx_{v_i} = \frac{1}{(fd_{v_i} \times rd_{v_i})}. \tag{6}$$

The probability of a data packet, successfully arrived at the recipient is called the forward delivery ratio and the reverse delivery ratio is the probability that the ACK packet is successfully received.

ETX of a route is the sum of the ETX of each link in the route and it is given by

$$ETX(P) = \sum_{i=1}^{n} etx_{v_i}.$$

The objective function for the minimum expected transmission count is given by

$$f_2 = \min \sum_{(i,j)\in E} T_{i,j} X_{i,j}. \tag{7}$$

3.3. Model constraints

A multiobjective optimization usually considers one or more constraints. In this model we have considered the flow conservation constraints.

3.3.1. Flow conservation

To ensure the consistency of the model, we have to model the flow conservation constraints on the origin, destination and intermediate nodes. The source node is denoted as 'S' and destination node as 'T'. The following equations are called the flow conservation constraints.

$$\sum_{(i,j)\in E} X_{ij} = 1, \quad i = S. \tag{8}$$

$$\sum_{(i,j)\in E} X_{ij} = -1, \quad i = T. \tag{9}$$

$$\sum_{(i,j)\in E} X_{ij} - \sum_{(i,j)\in E} X_{ji} = 0, \quad i \neq S, \quad i \neq T. \tag{10}$$

These restrictions aim to confirm that all data packets generated by nodes can reach the destination node and guarantee that the solutions obtained are valid paths from the origin 'S' to the destination 'T'.

4. Multiobjective evolutionary algorithm for routing problem

Multiobjective optimization can be solved by several methods, we have chosen MOEA because it has the ability to find multiple optimal solutions in one single simulation run [4]. NSGA-II is one of the most efficient and popular multiobjective evolutionary algorithm. In this paper, we propose MNSGA-II, an improved version of

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NSGA-II for solving the multiobjective routing problem. MNSGA-II algorithm uses non-dominated sorting for fitness assignments and dynamic crowding distance for improving the diversity. The new offspring is generated by using the partial mapped crossover (PMX), insertion mutation and binary tournament selection.

4.1. Chromosome representation

A chromosome corresponds to the possible solution of the optimization problem. A chromosome consists of sequences of positive integers that represent the IDs of nodes through which a routing path passes. A gene in a chromosome is characterized by two factors namely locus and allele. The locus represents the position of a gene located within the structure of chromosomes and allele represents the value that the gene takes. The length of the chromosome must not exceed the maximum length N, where N is the total number of nodes in the network. Thus, each chromosome represents a path which consists of a sequence of nodes and it starts with the source node followed by some intermediate nodes and the last node indicates the destination. MNSGA-II handles variable chromosome length.

4.2. Generation of initial population

There are two methods for generating the initial population heuristic initialization and random initialization. Random initialization is followed in this paper. The priority based encoding is used for generating the initial population and it was developed by Goldberg et al. [29]. In this encoding, the position of a gene is used to represent the node ID and its value represent the priority of the node for constructing a path among the candidates. A path can be determined uniquely by using this encoding. Every node is assigned a priority with a random mechanism and adds one with the highest priority into the path.

4.3. Crossover

Several crossover operators have been proposed for GA with permutation representation such as partial-mapped crossover (PMX), order crossover (OX), position-based crossover (PX), heuristic crossover, and so on [30]. We have adopted partial mapped crossover strategy proposed by Gen et al. [31] in this work. PMX can be viewed as an extension of two point crossover for binary string to permutation representation. It uses a simple repairing procedure to resolve the illegitimacy caused by the simple two point crossover. In PMX crossover, the repetition of nodes can be avoided by using a mapping function. Therefore, PMX finds many new paths without increasing computational complexity.

4.4. Mutation

Some mutation operators are easy to adopt the permutation representations such as swap mutation, inversion mutation, insertion mutation, and so on [30]. By avoiding the loss of heritability in permutation representation, we adopt insertion mutation to generate the offspring. Insertion mutation selects a gene at random and inserts it in another random position.

4.5. Dynamic crowding distance (DCD)

Most MOEAs use population maintenance to wipe off individuals when the number of non-dominated solutions exceeds population size. To remove the excess individuals, NSGA-II uses crowding distance (CD) measure as given in Eq. (11). The individuals having lower values of the CD are preferred over individuals with higher values of CD in removal process.

$$CD_i = \frac{1}{r}\sum_{k=1}^{r} |f_{i+1}^{r} - f_{i-1}^{r}|, \tag{11}$$

where r is the number of objectives. f_{i+1}^{k} is the kth objective of the $(i+1)$th individual and f_{i-1}^{k} is the kth objective of the $(i-1)$th individuals after sorting the population according to the CD. The major drawback of CD is lack of uniform diversity. To overcome this problem, dynamic crowding distance (DCD) method is suggested by Luo et al. [32].

In this approach, one individual with the lowest DCD value is removed every time and DCD is recalculated for the remaining individuals. The individual DCD is calculated as follows:

$$DCD = \frac{CD_i}{\log\left(\frac{1}{V_i}\right)}, \tag{12}$$

where CD_i is calculated using Eq. (11) and V_i is calculated using the Eq. (13)

$$V_i = \frac{1}{r}\sum_{i=1}^{r} (|f_{i+1}^{k} - f_{i-1}^{k}|CD_i)^2, \tag{13}$$

where V_i is the variance of CD_s of individuals which are neighbors of the ith individual. V_i can give some information about the different degree of CD in different objectives. This is illustrated below:

Let the population size is N, the non-dominated set at t-th generation is $Q(t)$ and the size of $Q(t)$ is M. If $M > N$, then use DCD to wipe off $M - N$ individuals from non-dominated set. The process of DCD is summarized as,

1. If $|Q(t)| \leq N$ then stop population maintenance else goto step 2.
2. Calculate all individuals' DCD in the $Q(t)$ based on Eq. (12).
3. Sort the non-dominated set $Q(t)$ based on individuals' DCD and wipe off an individual which has the lowest DCD in the $Q(t)$ and goto step 1.

4.6. MNSGA-II algorithm

The optimization process in MNSGA-II starts with a random population of solutions using priority based encoding. The flow diagram of MNSGA-II is given in Fig. 1.

The off-spring is generated by applying the genetic operators (i.e. PMX crossover and inversion mutation) to the parent population. Then the non-dominated sorting approach is applied on the combined population of parents and offspring. In this sorting procedure, all non-dominated solutions are ranked 1 and are temporarily removed from the population. The next set of non-dominated solutions in the population is then defined and ranked 2. The procedure is continued until all the solutions are ranked. Solutions at the same non-domination front are compared by a dynamic crowding distance, which is a measure by the solution's density at the neighborhood of that solution. The new population is generated by using the binary tournament selection to the current population. It randomly selects the two solutions for the current populations and choose the best one. The procedure is terminated when a user-defined maximum number of generations (MaxGen) is reached. Algorithm 1 gives the steps involved in implementing MNSGA-II.

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Algorithm 1. Modified Non-dominated Sorting Genetic Algorithm-II.

1. Set $t = 0$, $N = Population\_Size$.
2. Select ETX and MD values from OLSR routing table.
3. Generate initial population routes using priority based encoding.
4. P_t = Calculate the objective functions for the initial population.
5. Repeat.
6. Q_t = Generate offspring from P_t according to recombination and mutation operator.
7. $R_t = Q_t \cup P_t$.
8. F = Do Fast_non_dominated_Sorting (R_t), Obtaining different non_dominated fronts ($F_1, F_2, \ldots, F_n$).
9. Dynamic crowding_distance_assignment (F_i).
10. Apply the selection of routes based on the binary tournament selection.
11. $t = t + 1$.
12. Until $t < MaxGen$.

MNSGA-II algorithm is implemented by using an OLSR routing protocol. It is an optimization of the classical link state algorithm. It operates as a table driven, proactive protocol. Each node selects a set of its neighbor nodes as "Multipoint Relays (MPR)". In OLSR, the MPRs are selected nodes, which forward broadcast messages during the flooding process. This technique substantially reduces the message overhead and number of retransmission is required. MPR node may choose to report only links between itself and its MPR indicators. The expected transmission count and transmission delay can be calculated by changing the value of the following variant of the OLSR routing protocol.

$$Agent/OLSR \quad set \quad mpralgorithm = 2.$$
$$Agent/OLSR \quad set \quad linkquality = 2.$$
$$Agent/OLSR \quad set \quad linkdelay = true.$$

where mpralgorithm indicates the multipoint relay (MPR) selection algorithm that is going to be used, linkquality refers how the link quality metric will be computed and linkdelay indicates whether the minimum delay between nodes will serve as criteria for the selection of paths between them. In order to compute delay, we have used a variation of the CapProbe algorithm by Waverton et al. [27].

From these changes we can obtain each node in the network with the metric values such as ETX and delay for every link towards all other nodes at a given time. After finding the metric values, MNSGA-II algorithm is executed in the routing protocol.

4.7. Analytic hierarchy process (AHP)

Once solutions lying on the estimated Pareto-optimal set are found, it is usually required to choose one of them for implementation. From a decision maker's perspective, the choice of a solution from all Pareto-optimal solutions is called a posterior approach. It requires a higher-level decision-making approach which is to determine the best solution among a finite set of Pareto-optimal solutions with respect to all relevant attributes. Multiple attribute decision-making (MADM) techniques are generally employed in the posterior evaluation of Pareto-optimal solutions to choose the best one among them. A number of methods have been developed for selecting the best compromise solution in multiple attribute or multiple criteria problems. In this paper, analytic hierarchy process [8,33] is used to find the best compromise solution. Algorithm 2 gives the steps required in the proposed analytic hierarchy process.

Algorithm 2. Analytic hierarchy process.

1. Find the set of non-dominated solutions using MNSGA-II algorithm.
2. Compute the path–path pairwise comparison matrix($ppcm$) for every metric.
   $ppcm(i, i) = 1$, for same path;
   $ppcm(j, i) = 1/ppcm(i, j)$, for reciprocal paths;
   $ppcm(i, j) = m_j/m_i$, for min criterion.
   Here i, j are paths.
3. The normalized path–path pairwise comparison matrix($nppcm$) is calculated by
   $nppcm(i, j) = ppcm(i, j)/\sum ppcm\_column(j)$.
4. Average normalized priority path–path pairwise computation matrix($anppcm$) is done by
   $anppcm(i, j) = \sum nppcm_{row(i)} ./P$
5. The average normalized priority pairwise comparison matrix($anprpcm$) is assigned by equal priorities for every metric.
   $anprpcm = [0.5\ 0.5]$.
6. Calculate total score for each path as
   Path score $= \sum_{i=1}^{n} (anprpcm[i]^{*} anppcm[i, j]), \quad j = 1, \ldots, p.$
7. Select the path with the maximum total score as the best compromise solution.

5. Performance evaluation

To analyze the performance of MNSGA-II algorithm we consider the Optimized link state routing protocol (OLSR). In OLSR, the Multi-Point Relays (MPR) play a very crucial role in forwarding the packets. The node which chooses its MPR will forward the packets and reduce the redundant transmissions. The Fedora OS is used to run the simulation software NS2 (Network Simulator 2) version 2.34 for the evaluation. The patch for NS-2.34 to simulate the OLSR is given by Ross [35]. Simulation and Comparisons were conducted for two different scenarios. The first scenario consists of 20 nodes in random topology with 14 mobile nodes and 6 mesh routers. The second one is the 5×5 grid topology and consists of 25 mesh routers. The simulation parameters are shown in Table 1. Each simulation was run for 50 seconds and repeated 20 times. The average value with standard deviation is plotted as error graphs, The routing decision is made for considering the link qualities of both ETX and MD. The routing table is maintained for every node in the network and the metric values are stored for every link towards all other nodes at a given time.

5.1. Parameter tuning for MNSGA-II and R-NSGA-II

The performance of multiobjective evolutionary algorithm is sensitive to algorithm parameters. Hence it is needed to perform repeated simulations to find optimal values for the parameters. In this paper, optimal parameter combinations are experimentally determined by conducting a series of experiments with different parameter settings before conducting actual runs to get the results.

Table 1
Simulation parameters.

Parameters	Values
Simulation area	1000 m × 1000 m
Propagation model	Shadowing
IEEE standard	802.11*b*
Antenna model	Omni directional
Routing protocol	UMOLSR
Maximum number of packets in interface queue	60
Simulation duration	500 s
Number of nodes	20, 40, 60, 80, 100
Transmission range	250 m
Maximum mesh client speed	20 m/s
Traffic type	CBR
Mobility model for mesh clients	Random way point
Smoothing factor	0.4

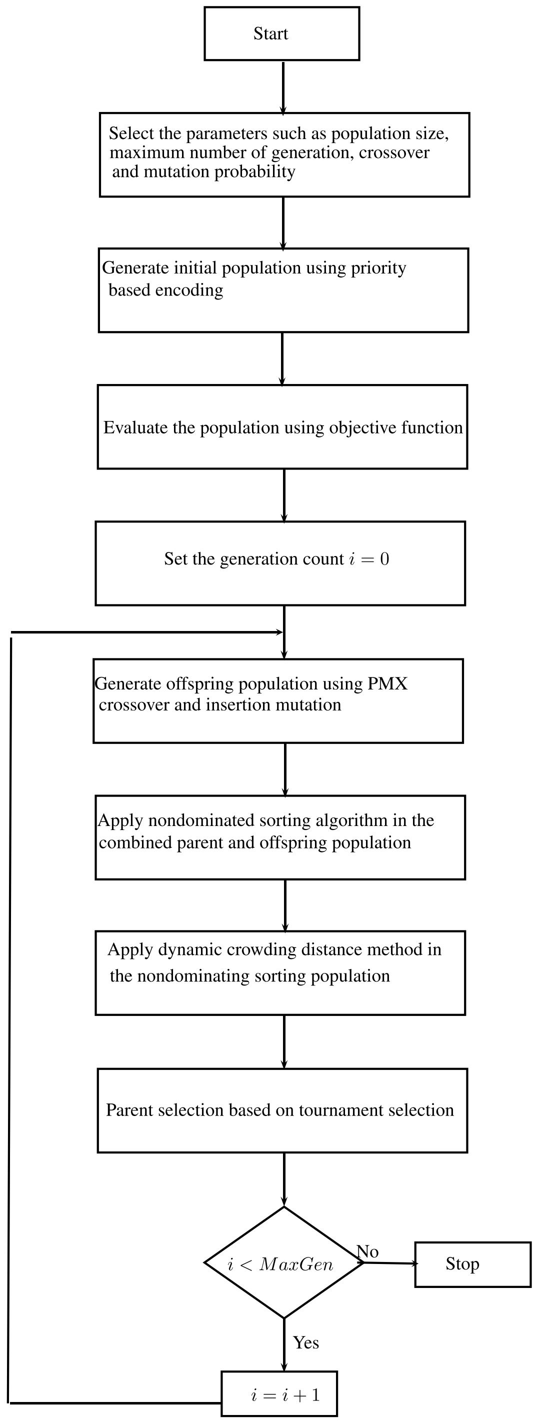

Fig. 1. Flowchart for MNSGA-II algorithm.

Table 2
Control parameters selected for MNSGA-II algorithm.

Parameters	Values
Population size	20
Number of generations	100
Crossover probability P_c	0.85
Mutation probability P_m	0.1
Selection of parents	Binary tournament
New generation selection	Elitist

The crossover probability (P_c) is selected between 0.5 and 0.95, in steps of 0.01 and for each P_c performance is analyzed. It is found that $P_c = 0.85$, produces the best results. Other parameters such as mutation probability (P_m) is selected between 0.1 to 0.3 and it is found that $P_m = 0.1$ produces the best result. Table 2 shows the set of control parameters selected after conducting the experiments.

5.2. Performance analysis

Fig. 2a shows the transmission delay for the 20 node network with 14 mesh clients and 6 mesh routers by varying the node mobility. MNSGA-II performs well compared to R-NSGA-II in case of low node mobility as well as the high node mobility. As the mobility of the nodes increases, the paths between communication end points will be broken frequently. In the proposed algorithm, the redundancy of nodes in the path can be avoided by using the mapping function of PMX crossover and hence there is no repair function is needed for selecting the path. It is clear that MNSGA-II has lesser delay than R-NSGA-II. Fig. 2b indicates the throughput for 20 nodes by varying the node mobility. In the proposed algorithm, the dynamic crowding distance method only wipes off one individual every time and recalculate the individual distance, so it provides more chance to retain the individual in the non-dominated set. Hence the throughput of MNSGA-II is higher than R-NSGA-II.

Fig. 3a plots the transmission delay comparison of MNSGA-II and R-NSGA-II algorithm with increase in the number of nodes and the speed of mesh client is 5 m/s. The initial population is encoded at random, the possibility of a feasible chromosome solution is less. In the proposed algorithm, the number of feasible solutions is increased by using priority based encoding and automatically it decreases the delay. It is observed that MNSGA-II performs better than R-NSGA-II.

Fig. 3b shows the throughput comparison of MNSGA-II and R-NSGA-II algorithm with increase in the number of nodes when the speed of mesh client is 5 m/s. While the number of nodes is increased, the proposed algorithm minimizes the expected number of transmission by using PMX crossover which indirectly improves the throughput. Hence MNSGA-II achieves higher throughput than R-NSGA-II.

The best Pareto-front is obtained among 20 simulation runs of random and static network using MNSGA-II and R-NSGA-II is shown in Fig. 4a and b. The Pareto front contains a set of trade-off solutions that are optimum from an "overall" standpoint, in a single run. Each solution in Pareto front provides a candidate optimal assignment of the WMN. It is observed from Fig. 4a and b that, MNSGA-II is able to maintain the solutions uniformly in the Pareto-optimal region. In MNSGA-II, the dynamic crowding distance algorithm calculates the individual dynamic crowding distance dynamically during the process of population maintenance. The dynamic crowding distance algorithm avoids some parts of the Pareto front which are excessively gathered. The other parts which are sparse obtain Pareto front with high uniformity thereby maintaining the diversity of the non-dominated set. MNSGA-II approach is capable of exploring more efficient and non-inferior solutions as compared to R-NSGA-II.

5.2.1. Posterior evaluation of Pareto optimal front

A decision-making procedure based on the analytic hierarchy process method is used to find the best compromise solution from the set of Pareto-solutions obtained using MNSGA-II and R-NSGA-II. Fig. 4a and b it clearly shows that the throughput and delay are lesser with MNSGA-II than R-NSGA-II. The best compromise solution using AHP for Fig. 4a is 6.7785 for throughput and 0.0545 for delay. It is obvious that MNSGA-II performs better than R-NSGA-II.

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