Application of Pareto optimality-based adaptive PSO to solve multicast type routing issues with multiple objectives

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Abstract

In network communication and distributed systems, numerous applications transmit data from the source to several destinations. The multicast routing is a remarkable combinatorial optimization issue with multiple objectives to optimize. Hybrid multi-objective evolutionary algorithms are employed for multicast routing. In this study, Pareto optimality-based adaptive PSO with variants are projected. The proposed algorithm and its variants optimize the cost, delay, and lifetime of the multicast tree. The aim is to construct a multicast type tree for transmitting data to minimize the cost, delay, and lifetime. Various strategies such as multi-objective weighted sum, dynamic inertia weight, adaptive non-dominated sorting approaches, and multi-objective local search based on the Pareto hill-climbing approach are implemented to identify the shortest path. The results are analyzed with respect to the cost, delay, and lifetime. The results of the ANS_MOPSO_PHC algorithm overtake the other techniques in this study.

Keywords: Nature-inspired, multicast routing, Meta-heuristics, Pareto optimal, Routing, Particle swarm optimization

1. Introduction

Presently the surging desire for the internet accelerated the prompt enlargement of networking applications. In network communication and distributed systems, aggressively there is a rising requirement for top-level data transmission. Understanding the network routing process is a vital research area. Network routing is classified into three types such as unicast, broadcast, and multicast. In unicast type, the data is sent from the source node to the challenging destination node. In broadcast type, the same data is sent to the other destinations in the network. In multicast type, the same data is transmitted to the specified set of destinations but not all destinations in the network. Unicast type performs one-to-one transmission whereas broadcast and multicast perform from a single source to many destinations. A huge number of live multimedia communication applications such as video conferencing, online gaming, online education, etc. operate in the multicast type routing.

Every day the present network communication deals with live multimedia applications for information transmission. The network technology for multimedia applications should be efficient and needs rapid network routing algorithms. These applications should satisfy the quality-of-service necessities. The requirement parameters are cost, delay, jitter, bandwidth,
and rate of packet loss. Multicast type routing is NP-hard and classified as a combinatorial optimization issue (Wang & Crowcroft 1996). Researchers globally adopt various techniques such as exact, heuristic and hybrid meta-heuristic for routing multicast type issues. A network weighted graph representation is created to minimize the multicast routing tree cost which fulfills the quality-of-service requirements. In the weighted graph, the route between the two nodes is identified as the shortest. Here, the shortest refers to the minimum total weight, where an edge between two nodes has a specific weight. The key objective is to identify and create the shortest route in the computer network between the source and destination based on the requirements of delay, packet loss rate, jitter, and bandwidth.

The purpose of this study is to seek the ideal multicast routing path to transfer the multimedia data from source to destination in MANETs. The multicast routing problem can be answered with the help of hybrid multi-objective meta-heuristics optimization techniques. A set of possible solutions are present in the discrete or continuous search space in these optimization techniques. Hybrid multi-objective meta-heuristics algorithms are applied to attain solutions to routing multicast type issues in MANETs. The multi-objective PSO with the variants is proposed to enhance the routing task.

The significant research contributions of this study are recorded below:

i) A hybrid multi-objective PSO and its four variants are proposed to perform multicast type routing for multimedia data communication applications from source to a destination node in MANETs.

ii) A multicast type tree is constructed for data transmission by minimizing the delay, CPU time, and cost requirements.

iii) PSO variants such as multi-objective weighted sum, dynamic inertia weight, and adaptive non-dominated sorting approaches are applied to identify the shortest path in the computer network.

iv) To exploit the search space efficiently a multi-objective local search based on the Pareto hill-climbing approach is applied to optimal solutions with stated probability. Various other strategies such as elite conserving and learning aspects also are applied.

v) The proposed approaches are analyzed for cost, delay, and CPU duration. Results are compared to related existing techniques.

The paper is structured as follows. Section 2 provides the review of related work. The framework of multi-objective optimization, non-dominated sorting, and Pareto optimality is described in section 3. The problem description, multi-objective particle swarm optimization, its variants, and several proposed strategies are elaborated in section 4. The experimental results are presented in section 5. Section 6 discusses the conclusion.

2. Related work

Numerous multicast-type routing algorithms in MANET have been intended by several researchers. There is a requirement in various live multimedia communication applications for top-level data transmission from source to many destinations. Optimizing the shortest routing
path in the multicast type routing technique is a difficult task. Hence, there is a growing demand for top-level data transmission multicast type routing techniques. This section deliberates some of the related techniques based on the meta-heuristics optimization to solve the issues in multicast type routing.

Researchers study numerous GAs to answer the multicast type routing issue. Hwang et.al (2000) came up with a novel multicast routing technique using GA. New methods are applied to the actual networks to minimize the computational complexity. The optimized path is achieved in the multicast tree by performing operations like selection, crossover, and mutation. The results of the proposed technique are better when compared with the RSR algorithm. Zhengying et al (2001) came up with a multicast routing technique using a genetic algorithm to solve bandwidth and successive delay requirements. The multicast tree is optimized with minimum cost for independent metrics like delay and cost. GA’s encoding process is improved, and the crossover and mutation operators are enhanced. The result of the proposed technique is efficient and effective. Haghighat et al. (2003) developed a novel technique for QoS multicast routing based on GA to create a multicast tree with minimum cost. The delay and bandwidth are the constraints employed. Performance is assessed and related to existing algorithms. The result of the intended technique outperforms the other algorithms. Sun et al. (2008) introduced a novel version of the optimization algorithm in MANET for QoS multicast type routing using GA. The multiple constraint multicast routing optimizes the maximum link usage, multicast tree cost, path selection, average delay, and nonstop delay. The results of this approach are efficient and accurate and it aids to evaluate the path stability in dynamic networks.

Researchers study several particle swarm optimization to answer the multicast type routing issue. Liu et al. (2006) developed an approach to answering the multicast type routing issue using PSO. A penalty function is introduced, and a novel integer coding is constructed with a few constraints or serial path selections in a multicast tree by converting it into a quasi-continuous issue. The paths are exchanged in the vector to find the optimal solutions with minimum computational cost. The results of PSO outperform GA in routing multicast based on QoS. A quantum PSO with an enhanced version for QoS routing in multicast type is developed by Sun et al. (2011). The problem is transformed into an integer with QoS by combining with loop deletion operation. The proposed method is validated on randomly generated network topologies. The simulation results of the intended approach is superior to the existing GA and PSO approaches.

Qu et al. (2013) came up with a jumping PSO for solving constrained routing of multicast type issues. The model used to solve the problem is the Steiner tree structure produces significant results using meta-heuristics techniques. To enhance the particle’s position a novel path replacement operator is introduced in the PSO algorithm to obtain optimal results and the local search operator is integrated with the jumping PSO algorithm. Experimental results of jumping PSO technique are superior to former advanced techniques. Shen et al. (2014) introduced a new bi-velocity discrete PSO technique for routing multicast type issues. The particle representation is from continuous to the binary or discrete domain. Initially, the strategy is described in binary representation where 1 denotes the node is selected and 0 denotes the node is not selected. Next, the velocity and position of the particles are updated in the continuous domain. This aids
in faster convergence and attains performance searchability. The experiments are conducted using 58 data instances and the simulation results of the proposed approach outperform the GA, ACO, and prior PSO techniques.

Tseng et al. (2008) introduced a novel technique for broadcasting problems based on ant colony optimization. The various constraints are degree and delay with minimum cost in the network. The results exhibit the ability of the intended approach. Wang et al. (2011) developed a novel optimization tree approach for routing multicast type with QoS using an ant colony algorithm. Here, an optimization technique is applied to control the growth of the tree to create a multicast type tree. The objective is to minimize limitations like cost, delay, bandwidth, and jitter. The performance of the intended technique is evaluated and compared with the existing techniques like GA and Tabu Search. The results of the intended technique are better with reference to convergence speed, search, and adaptability.

Youssef et al. (2002) introduced the tabu search technique by creating a low-cost routing tree in multicast type. The QoS requirements such as delay constraint are considered and a minimum cost multicast type tree is constructed. Experiment results exhibit those better solutions are identified by the intended approach than other existing multicast type approaches. Ghaboosi and Haghighat (2007) created a tabu search approach for constructing a multicast type tree for two vital constraints like bandwidth and end-to-end delay. Various issues like selecting the initial solution and handling the local optimum solutions. The performance is evaluated and efficiency is compared with other heuristic techniques on randomly generated networks. The experiment results exhibit the combined strategies are supportive to produce a low-cost multicast tree. Wang et al. (2010b) came up with a novel selection technique called rendezvous point in the Tabu search algorithm. The cost and delay constraints are considered in the center selection issue. A multicast tree is constructed for the multicast type data transmission. The rendezvous point is selected based on the TS algorithm in the multicast routing with delay and cost as parameters. Superior output is achieved in register and end-to-end delay and cost. Misra and Rajesh (2011) introduced a routing protocol using a bird-inspired technique formed on routing position. The birds’ navigating prolonged distances is the inspiration for generating this protocol. The navigation is based on the distance vector and most forward distance routing protocols. The results are compared with AODV protocols and it shows that the intended technique is robust and accessible with minimum nonstop delay.

Zhang et al. (2009) developed a technique that combines GA and simulated annealing algorithms for solving multicast type routing issues. The tree structure chromosome representation is performed for the multicast tree. The adaptive crossover technique is applied to enhance the efficiency of the algorithm. The results illustrate that quick convergence and search efficiency is achieved in the proposed technique compared to GA and SA hybrid techniques. Xing et al., (2009) came up with an enhanced algorithm by combining multi-granularity and quantum genetic algorithms for multicast type routing issues. A quantum mutation operator is introduced to handle the local search effectively. A repair strategy is applied to remove the unwanted paths hence, more number of optimal solutions are produced. Simulation results illustrate that the proposed approach is robust, searchability is excellent, and quick convergence also overtakes the existing approaches. Wang et al., (2010a) present a tree-
based routing algorithm using PSO with minimum cost to satisfy the delay, bandwidth, and delay jitter constraints. The algorithm identifies the path and integrates the solutions to produce a multicast tree. Experiment results illustrate that the intended technique outperforms with respect to search, accessibility, and convergence speed.

Xi-hong et al., 2010 introduced a combination technique with PSO and ACO aimed at routing multicast types. The position updating operation in PSO technique is based on the solutions produced by ACO. The results of the hybrid technique meet the constraints of the multicast type routing issue. Abdel-Kader, 2011 developed a combination approach with GA and PSO for routing multicast type with QoS. Two parameters are used to adjust and optimize the hybrid model. The hybrid model overcomes the demerits of the PSO and GA approaches. The results of the combined approach outperform the standard individual models. Patel et al., 2014 introduced another merging technique with PSO and ACO for routing multicast types Results contain global superior solutions when compared to TGBACA and PSOTREE approaches. Moheb et. al (2016) came up with yet another merging technique with GA and PSO for routing multicast types with minimum costs and other constraints. The intended method outcome is optimal than GA and PSO approach. Mahseur and Boukra (2017) came up with a hybrid approach by combining BBO and BA. The results of the hybrid technique are superior to other existing techniques. These are all the various existing approaches for resolving multicast routing issues with multiple constraints.

3. Framework of Multi-objective optimization, non-dominated sorting, and Pareto optimality

In this section, an outline of the multi-objective optimization problem, non-dominated sorting, and Pareto optimality is described.

3.1 Multi-objective optimization problem

A set of Pareto optimal solutions are present in the multi-objective optimization problems though all the objectives are observed concurrently Coello et.al (2007). To simplify the problem, it is assumed to minimize all the objectives. MOO problem tries to enhance \( k ( \geq 2) \) objectives concurrently. \( f_i (x) | 1 \leq i \leq k \) To achieve ‘x’ feasible decision vector satisfies ‘h’ constraints \( c_i (x) \geq 0 | 1 \leq i \leq h \) defined as:

\[
\text{Minimize: } f(x) = \{ f_1(x), f_2(x), ..., f_k(x) \} \mid x \in X \\
\text{Subject to: } \{ c_j(x), c_{j_1}(x), ..., c_{j_h}(x) \} \geq 0
\]

where ‘X’ is the decision vector set.

3.2 Non-dominated sorting

Subsequent iterations are used to identify solutions by categorizing the population. Various sorting steps are i) for each solution ‘p’ and ‘q’ in population ‘N’, ii) If \( q \neq p \), compare ‘p’ and ‘q’ for all ‘m’ objectives, iii) For any ‘q’, ‘p’ is dominated by ‘q’ and spot solution ‘p’ as dominated. The solutions unmarked are named as non-dominated. It forms the first front non-dominated population. This procedure is continued for the left over solutions and further
advanced non-dominated fronts before the complete population is categorized into varied fronts.

3.3 Pareto optimality

The various definitions of Pareto optimality (Liang et.al 2018, June) are:

Pareto dominance: A \( x \in X \) decision vector is assumed to govern \( y \in Y \) another vector, (mentioned as \( x \ p \ y \)) provided ‘\( x \)’ decision vector is equivalent or beyond ‘\( y \)’ for each objective and ‘\( x \)’ is beyond ‘\( y \)’ for not less than one objective. That is
\[
\forall i: f_i(x) \leq f_i(y) \land \exists i: f_i(x) < f_i(y) \mid 1 \leq i \leq k
\]

Pareto optimal: A decision vector ‘\( x \)’ is said to be Pareto optimal provided if there does not exist ‘\( y \)’ any other decision vector so that ‘\( y \)’ dominates ‘\( x \)’ that is \( y \ p \ x \).

Pareto optimal set: Set of all feasible Pareto optimal solutions and is denoted as:
\[
PS = \{ x \in X \mid \neg \exists y \in X : y \ p \ x \}
\]

Pareto front: A value of each Pareto optimal solution in the Pareto optimal set that is:
\[
PF = \{ f(x) \mid x \in PS \}
\]

4. Multi-objective PSO and its variants for routing multicast type problem

This section deals with the problem description, multi-objective particle swarm optimization, its variants and several strategies to enhance the solution quality.

4.1 Problem Description

The problem is termed as identifying the optimal path between source and destination in the network. The multicast type routing tree is discovering the path between two nodes in a weighted graph. Finding the shortest route refers to the path with minimum total weights. This combinatorial optimization problem is recognized as an NP-complete problem (Drake & Hougardy 2004) where a Steiner tree is built and can be solved using heuristic algorithms. In this study, a communication system is modeled as \( G = (N, E) \) denotes a weighted graph with vertices \( (N) \) and edges \( (E) \) which denotes a network with nodes \( |N| \) and links \( |E| \). The multicast type tree from the source node is denoted as \( s_n \) to the set of destination nodes denoted as \( UD = \{ud_1, ud_2, \ldots, ud_m\} \). In multicast type tree let \( X = \{sn_0, ud_1, ud_2, \ldots, ud_m\} \in N \) denote a set from source to destination nodes. \( MT = (N_M, E_M) \), is a multicast type tree here, \( N_M \subseteq N \) and \( E_M \subseteq E \), a path \( P_{MT}(n_0, d) \) source node \( sn_0 \) \( P_{MT}(n_0, d) \) to \( d \in U \) destination in MT. Three real value functions for cost, delay, and hop are related for each link \( e(e \in E) : C(e), D(e), \) and \( H(e) \) are non-negative. The link cost function denoted as \( C(e) \) is either financial cost or any amount of resource consumption. The link delay \( D(e) \) denotes the criteria and the link hop \( H(e) = 1 \) denotes the number of hops.

The sum of the cost of all links in that path is the cost of the path \( P_{MT} \) and can be specified as
The sum of the cost of all links in that tree is the total cost of the tree \( MT \) and can be specified as

\[
C(MT) = \sum_{e \in E_{MT}} C(e)
\]  

(7)

The sum of the delay of all links is the total delay of the path \( P_{MT}(sn_0, d) \) along with \( P_{MT}(sn_0, d) \) given by

\[
D(P_{MT}) = \sum_{e \in P_{MT}(sn_0, d)} D(e), \ d \in UD
\]  

(8)

Maximum delay rate path from \( sn_0 \) source to \( d \in UD \) each designation is the delay of the multicast tree \( MT \).

\[
D(MT) = \max \left( \sum_{e \in P_{MT}(sn_0, d)} D(P_{MT}), d \in UD \right)
\]  

(9)

The sum of the hop of all links in that path is the hop of the path \( P_{MT} \) and can be specified as

\[
H(P_{MT}) = \sum_{e \in P_{MT}} H(e)
\]  

(10)

The sum of the hop of all links in that tree is the hop of multicast tree \( MT \) and can be specified as

\[
H(MT) = \sum_{e \in E_{MT}} H(e)
\]  

(11)

The \( SW(P_{MT}) \) vector of the path \( P_{MT} \) consists of the vector sum of the vectors equivalent to arcs

\[
SW(P_{MT}) = C(P_{MT}) + D(P_{MT}) + H(P_{MT})
\]  

(12)

The problem objective is to identify the multicast type routing tree \( MT \) which minimizes the cost \( C(MT) \), delay \( D(MT) \), and hop \( H(MT) \). The problem is formulated as shown below:

\[
W(MT) = \sum_{e \in E_{MT}} C(MT) + D(MT) + H(MT)
\]  

(13)

Where \( W(MT) \) is the weight of multicast type routing tree \( MT \). The cost \( C(MT) \), delay \( D(MT) \), and hop \( H(MT) \) are defined in the equations (7), (9) and (11).
4.2 Multi-Objective Particle Swarm Optimization (MOPSO), its variants and several strategies to enhance the solutions

The PSO algorithm is relatively simple and it’s a population-based technique can be implemented with multiple objectives to be optimized. It is a Pareto based method which uses selection approach for Pareto dominance. This section elaborates on the MOPSO and its variants.

4.2.1 Multi-Objective Weighted Sum Particle Swarm Optimization (MOWS_PSO)

Each particle signifies a possible solution in MOPSO. Supposing there are ‘N’ particles in the swarm with n-dimensional search space. The position and velocity of the particle ‘i’ are represented as $x_i = (x_{i1}, x_{i2}, ..., x_{in})$ and $v_i = (v_{i1}, v_{i2}, ..., v_{in})$ correspondingly. They are updated as follows:

$$v_i(t+1) = w_v v_i(t) + c_1 r_1 (pbest_i - x_i(t)) + c_2 r_2 (nbest_i - x_i(t))$$  \hspace{0.5em} (14)

$$x_i(t+1) = x_i(t) + v_i(t+1)$$ \hspace{0.5em} (15)

Where ‘t’ denotes the iteration, ‘w’ is weight inertia, ‘c1’ and ‘c2’ denotes the acceleration constants, ‘r_1’ and ‘r_2’ denotes the random variables range (0,1), ‘pbest’ and ‘nbest’ denotes the positions of personal best and neighbour best in the ‘i’th particle. The huge inertia weight aids in global investigation while the lesser inertia weight aids in reasonable modification of the present search space. Inertia weight is given below:

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} x t$$ \hspace{0.5em} (16)

Where ‘$w_{max}$’ and ‘$w_{min}$’ are initial and final weight. ‘$iter_{max}$’ denotes the total iteration count and ‘t’ denotes the present iteration number.

4.2.2 Non-dominated Sorting Multi-Objective Particle Swarm Optimization (NS_MOPSO)

To assist multi-objective method to PSO, the concepts of Pareto-optimal and non-dominated sorting are combined (Li 2003). To utilize valued non-dominated differentiations by updating (pbest). NS_MOPSO combines ‘N’ particles and its offspring to create 2N particle population. Finding different non-dominated fronts with these 2N particles and assigning the fitness value to the fronts they fit in the population. Ranking values are given to the individuals in the non-dominated population and Crowding Distance (CD) procedures are applied to maintain the population diversity. The ‘pbest’ and ‘nbest’ are updated using the fitness and CD value of ‘N’ particles. The step by step process of NS_MOPSO are given below.

i) Preliminary population ‘N’ is created. Particle’s position and velocity are randomly initialized

ii) NS and CD population ranking is performed.
iii) Rank value equal to non-dominated level is assigned to each individual.
iv) One individual as ‘nbest’ is chosen randomly from the ND solutions of best fronts.
v) New velocity and location is determined using ‘pbest’ and ‘nbest’.
vi) New position and ‘pbest’ are joined to create a lengthy population size (2N).

4.2.2.1 Elite conserving strategy

In the elite conserving strategy, elite solutions of a population are directly transferred to the next generation. The non-dominated solutions identified in each generation are moved to the next generations till the other solutions dominate them.

4.2.2.2 Crowding distance calculation

To assess the compactness of solutions neighbouring a specific solution crowding distance is calculated based on the objectives. Average distance of two solutions on both sides of the neighbouring solutions is compared with various crowding distances. If \( f_j^i \) is j\(^{th}\) value of objective function for \( i^{th}\) individual, maximum value \( f_j^{\text{max}} \) and minimum value \( f_j^{\text{min}} \) is j\(^{th}\) function. The crowding distance of the \( i^{th}\) individual is defined as the average distance between the two nearby solutions and is given in equation (17)

\[
\text{cd}(i) = \frac{1}{k} \sum_{j=1}^{k} \frac{f_j^{i+1} - f_j^{i-1}}{f_j^{\text{max}} - f_j^{\text{min}}}
\]

(17)

Where ‘\( k \)’ is the number of objective functions.

4.2.3 Adaptive Non-dominated Sorting Multi-Objective Particle Swarm Optimization (ANS_MOPSO)

The ANS_MOPSO incorporates dynamic ‘w’ inertia weight and learning aspects C1 and C2 strategies.

4.2.3.1 Learning aspects Strategy

To compromise better between exploration and exploitation of the search space, acceleration coefficients are introduced in PSO algorithm. Improved solutions with Pareto optimality are produced when \( C_1 \) is reduced from primary value \( C_1(i) \) to \( C_1(f) \), \( C_2 \) is increased from this \( C_2(i) \) value to \( C_2(f) \). The values of \( C_1 \) and \( C_2 \) are given below:

\[
C_1(t) = (C_1(f) - C_1(i)) \cdot \frac{t}{T} + C_1(i)
\]

(18)

\[
C_2(t) = (C_2(f) - C_2(i)) \cdot \frac{t}{T} + C_2(i)
\]

(19)

4.2.3.2 Dynamic Inertia weight Strategy
The convergence quality in PSO algorithms depends on the dynamic inertia weight. The search algorithms which are population based depends on the global exploration and local exploitation. The initial phase focuses on exploration and later phases focuses on exploitation for optimal results. Thus the crowding distance is calculated in the proposed approach. The \( w \) is reduced from \( w_{\text{max}} \) to \( w_{\text{min}} \). Dynamic weight is calculated as shown below:

\[
  w(t) = (w_{\text{max}} - w_{\text{min}}) \frac{T - cd}{T} + w_{\text{min}} e^{-cd}
\]

where, \( T \) is maximum iteration count, \( t \) is present iteration and \( cd \) is the crowding distance.

4.2.4 Integrated ANS_MOPSO with Pareto Hill Climbing technique (ANS_MOPSO_PHC)

An integrated multi-objective optimization algorithm using PSO with Pareto hill climbing approach is proposed (Subashini & Bhuvaneswari 2012). For exploration PSO approach is used and for exploitation multi-objective local search approach is applied. The impact of exploitation is a local search technique combined with PHC approach for obtaining optimal solutions with stated possibility. PHC approach is applied to various fronts of selected number of ‘pbest’ solutions. In PHC method, mutation is performed by creating neighbourhood for every solution. The chosen and other solutions are compared in the neighbourhood for non-dominated set. If better solution exist in the neighbourhood, then definite solution is substituted with better solution. This process is repeated for numerous generations on each chosen ‘pbest’. This approach aids in superior exploitation of the search space. Figure 1 describes the process of the ANS_MOPSO_PHC technique.

4.3 Solution representation, encoding scheme and initialization

In this study, a possible solution is represented as a particle population with ‘n’ dimension and ‘n’ nodes. Each particle is represented as a single tree with length of each particle varies based on the position and velocity vectors. In the position vector, the preliminary encoding of the solutions is in the form of continuous value. However, the tree for routing can be denoted in the sequences of discrete vector. Hence, it’s necessary to convert this continuous vector into discrete vector. The Smallest Position Value (SPV) approach is used to sort the position vector values in ascending order and their corresponding indexes are used as discrete value. For ‘n’ nodes and ‘m’ destinations, each particle signifies a possible routing. For example, in a network consisting of 10 nodes, the nodes are placed arbitrarily. The position vector \( x_i = (x_{i1}, x_{i2},...,x_{in}) \) consists of continuous value set. By applying SPV approach, continuous location vector is transferred into sequence \( s_i = (s_{i1}, s_{i2},...,s_{im}) \). The operation vector \( r_i = (r_{i1}, r_{i2},...,r_{im}) \) denotes the operation vector defined as \( s_j = r_i \mod m \). Routing path for ‘n’ nodes represents this sequence. Table 1 represents particle’s \( x_i \) solution representation for ANS_MOPSO technique with 5 nodes.

<table>
<thead>
<tr>
<th>Table 1 Particle representation in ANS_MOPSO technique</th>
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<tr>
<td>Dimension</td>
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<td>2</td>
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<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
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</tbody>
</table>

### 4.4 Fitness Function

To identify a multicast tree by reducing the cost function to fulfils QoS requirements such as cost, delay and hop. The fitness function to minimize the multicast tree cost is given below:

$$f(MT) = \text{Minimize}(W(MT))$$  \hspace{1cm} (21)

where

$$W(MT) = \sum_{e \in E_{mt}} C(MT) + D(MT) + H(MT)$$  \hspace{1cm} (22)

1. Initialize population N and allocate to ‘pbest’.
2. Execute non-dominated sorting and crowding distance ranking.
3. Randomly select ‘nbest’ from top Front 1.
4. Update particle’s location and velocity.
5. Combine updated particles and procedure population of 2N size.
6. Execute non-dominated sorting for 2N and identify ND fronts to calculate CD.
7. Select N in Front 1 and set ‘pbest’.
8. Select X out of N and perform PHC process.
10. If better solutions exist replace selected ‘pbest’ with better solutions else retain the solutions.
11. If the terminating criteria for PHC is achieved goto step 12 else goto step 9.
12. If the terminating criteria for ANS_MOPSO_PHC is achieved terminate else goto step 3.

**Figure 1 Workflow of ANS_MOPSO_PHC technique**

### 5. Test Results and Discussion

In this section, network model, simulation environment, algorithm parameters, experimental results, performance analysis of the proposed techniques and the comparative analysis with the existing approaches are presented.

To demonstrate the usefulness of MOPSO and its four variants, experiments are conducted for the network topology generated using Waxman’s random graph (Salama et al., 1997). The simulations are performed using an Intel Core i5 CPU with 3.4 GHz, 8.00 GB RAM and windows 7(64 bit). The intended algorithm and its variants are implemented using C#
programming language. The performance of the intended algorithm is analysed by conducting various set of experiments consisting of different size network nodes. Due to stochastic nature of multi-objective evolutionary optimization algorithms, it is executed ten times independently and the results are analysed. Table 1 provides the parameters of MOPSO and its variants.

### Table 1 Parameters of MOPSO and its variants

<table>
<thead>
<tr>
<th>Parameter</th>
<th>MOWS_PSO</th>
<th>NS_MOPSO</th>
<th>ANS_MOPSO</th>
<th>ANS_MOPSO_PHC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>200</td>
<td>200</td>
<td>200</td>
<td>200</td>
</tr>
<tr>
<td>Number of generations</td>
<td>700</td>
<td>700</td>
<td>700</td>
<td>500</td>
</tr>
<tr>
<td>$C_1$</td>
<td>2</td>
<td>2</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>$C_1(i) = 2.5$</td>
<td>$C_1(i) = 2.5$</td>
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<td></td>
<td></td>
<td>$C_1(f) = 0.5$</td>
<td>$C_1(f) = 0.5$</td>
</tr>
<tr>
<td>$C_2$</td>
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<td>2</td>
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<td></td>
<td></td>
<td>$C_2(i) = 0.5$</td>
<td>$C_2(i) = 0.5$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$C_2(f) = 2.5$</td>
<td>$C_2(f) = 2.5$</td>
</tr>
<tr>
<td>$W_{\max}$</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>$W_{\min}$</td>
<td>0.4</td>
<td>0.4</td>
<td>0.4</td>
<td>0.4</td>
</tr>
<tr>
<td>Neighbourhood size</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>5</td>
</tr>
</tbody>
</table>

### 5.2 Simulation Results

In this experiment, the total nodes in the network was fixed as 10, 20 and 30. Table 2 illustrates the non-dominated solutions attained by randomly chosen Pareto sets achieved by the MOWS_PSO, NS_MOPSO, ANS_MOPSO and ANS_MOPSO_PHC algorithms respectively. The bold values in Table 2 represents the solutions that dominates the other solutions for varied network size. It is observed that the ANS_MOPSO_PHC technique achieves solutions dominating the MOWS_PSO, NS_MOPSO and ANS_MOPSO techniques in the network size of 10, 20 and 30 for cost factor. In the network size 30, the ANS_MOPSO technique achieves solutions dominating the MOWS_PSO, NS_MOPSO and ANS_MOPSO_PHC techniques for delay factor. In the network size 10 and 20, the MOWS_PSO technique achieves solutions dominating the NS_MOPSO, ANS_MOPSO and ANS_MOPSO_PHC techniques for CPU time factor. In the network size 30, ANS_MOPSO_PHC technique achieves solutions dominating the MOWS_PSO, NS_MOPSO and ANS_MOPSO techniques for CPU time factor.

### Table 2 Non-dominated solutions attained by the MOPSO and its variants

<table>
<thead>
<tr>
<th>Network size</th>
<th>Algorithm</th>
<th>Cost</th>
<th>Average Delay</th>
<th>CPU Time</th>
</tr>
</thead>
</table>


<table>
<thead>
<tr>
<th></th>
<th>MOWS_PSO</th>
<th>NS_MOPSO</th>
<th>ANS_MOPSO</th>
<th>ANS_MOPSO_PHC</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>51.8742</td>
<td>62.872</td>
<td>21.33</td>
<td><strong>49.2501</strong></td>
</tr>
<tr>
<td></td>
<td>52.1934</td>
<td>61.903</td>
<td>21.58</td>
<td>51.1023</td>
</tr>
<tr>
<td></td>
<td>49.2501</td>
<td>61.025</td>
<td>23.31</td>
<td>49.2501</td>
</tr>
<tr>
<td>20</td>
<td>55.871</td>
<td>62.251</td>
<td><strong>7.63</strong></td>
<td>54.004</td>
</tr>
<tr>
<td></td>
<td>55.890</td>
<td>62.461</td>
<td>8.30</td>
<td><strong>54.149</strong></td>
</tr>
<tr>
<td></td>
<td>54.004</td>
<td><strong>61.512</strong></td>
<td>8.89</td>
<td>54.004</td>
</tr>
<tr>
<td>30</td>
<td>62.913</td>
<td>66.305</td>
<td>5.33</td>
<td><strong>59.511</strong></td>
</tr>
<tr>
<td></td>
<td>62.015</td>
<td>65.024</td>
<td>4.96</td>
<td><strong>61.421</strong></td>
</tr>
<tr>
<td></td>
<td>61.421</td>
<td><strong>63.590</strong></td>
<td>5.07</td>
<td><strong>61.421</strong></td>
</tr>
<tr>
<td></td>
<td><strong>59.511</strong></td>
<td>63.972</td>
<td><strong>4.71</strong></td>
<td><strong>59.511</strong></td>
</tr>
</tbody>
</table>

Finally, the convergence property chart of cost for 10 nodes is presented in Figure 2 for all the algorithms. The convergence speed is quick in ANS_MOPSO_PHC than the other techniques. The convergence property chart of life time for 30 nodes is presented in Figure 3 for all the algorithms. It is clearly understood from the graphs that the convergence is fast in ANS_MOPSO_PHC than the other techniques which describes that the ANS_MOPSO_PHC approach has durable search ability than the other approaches in this study.

![Figure 2](image-url)
6. Conclusion

The present investigation addresses routing issue with multicast type based on Pareto optimal adaptive particle swarm optimization and its variants. The QoS requirements considered for data transmission are cost, delay and lifetime. To demonstrate the consistency and competence of the proposed techniques, the experiments are carried out for numerous network sizes. The proposed technique uses encoding scheme which converts the continuous vector into discrete vector. The non-dominated sorting is performed and strategies such as elite conserving is applied. The results attained by the intended algorithm are compared with its other variants and analysed. The results produced by the ANS_MOPSO_PHC approach is robust, and the convergence is rapid compared to the other techniques. The scalability of the algorithm is also verified. The future work can deal with the other aspects of multi-objective problem and the various network models can be taken into consideration.

Declarations

1) Ethics approval and consent to participate
This study did not include Human participants or Patient data. Hence no ethical approval and consent to participate is required.

2) Consent for publication
Not applicable. This study did not include patients.

3) Availability of data and materials
All data generated or analyzed as part of this study are included in this published article.

4) Competing interests
The authors declare that they have no competing interests.
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6) **Authors' contributions**
all authors' individual contributions, using the relevant CRediT roles:

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- Data curation: Ahmed A. Elngar
- Formal analysis: Harihara Gopalan S
- Investigation: Ahmed A. Elngar
- Methodology: Harihara Gopalan S
- Project administration: Ahmed A. Elngar
- Resources: Harihara Gopalan S
- Software: Harihara Gopalan S
- Supervision: Ahmed A. Elngar
- Validation: Ahmed A. Elngar
- Visualization: Ahmed A. Elngar
- Roles/Writing - original draft: Harihara Gopalan S
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References


problems. In International Conference on Swarm Intelligence (pp. 550-560). Springer, Cham.


