

Amalgamated Evolutionary Approach for Optimized Routing in Time Varying Ultra Dense Heterogeneous Networks

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ABSTRACT

Routing mechanisms in ultra-dense networks (UDNs) are expected to be flexible, scalable, and robust in nature, and the establishment of the shortest path between the source and destination pairs will always be a critical challenge. Through this projected work, the optimized shortest route of different source-destination pairs is found using a class of evolutionary optimization algorithms, namely PSO, GA, and the proposed hybrid PSO-Genetic Mutation (PSO-GM) algorithm, which searches for an optimized solution by representing it as a shortest path routing (SPR) problem. The key attribute of the PSO-GM approach is related to the application of an amalgamated strategy with Gaussian, Cauchy, Levy, single-point, and chaos mutation operators. Simulation results and application of the above-mentioned algorithms to the SPR problem in UDNs reveal that the hybrid PSO-GM algorithm provides a comparatively enhanced optimized solution. In the case of the rate of convergence to the theoretical limit, the hybrid PSO-GM gives 20% better results compared to the PSO and GA.

KEYWORDS

5G, Evolutionary Programming, Genetic Algorithm, Hybrid PSO-GM, Mutation Operators, Particle Swarm Optimization, Routing, Shortest Path Routing Problem, Ultra-Dense Network

INTRODUCTION

The exponential growth and accessibility of data in multiple forms is the main driving force for the continuous development of the communication industry. With each passing day, the ever increasing demand for smart devices, mobile multimedia services like e-healthcare, video conferencing, video surveillance, online gaming with High Definition (HD) and Ultra High Definition (UHD) Resolution video, etc. is only rising rapidly. This defines a new phase of development of mobile communications (Kamel et al., 2016). The extraordinary amount of data traffic generated by today's user requires a fundamental change in all aspects of mobile networks. Many international forecasting agencies project that there shall be around 40 billion wireless connected Internet of Things (IoT) devices by 2025. The 5G cellular networks shall usher in an epoch with over 1Gbps connectivity, around 1ms latency,

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50MHz bandwidth, etc. Ultra Dense Network (UDN) is a new paradigm shift in the direction of 5G cellular networks and realization of its true potential. Hence, UDNs are evolving as one of the core challenges and research areas of 5G cellular networks that would bring in far reaching modifications in future networks (Yu et al., 2016).

In UDNs, the mobile end user clients would operate on a large number of densely deployed small cells and access nodes in their indoors like buildings, homes or in outdoor hotspot areas like airports, trains, metro/train stations, etc. Small cell networks will synchronize with macro cells, either in the same spectrum or on a dedicated carrier channel.

Figure 1. A generic UDN with mobile users/relay nodes as source/destination pairs and the network is densified with large numbers of small cells of varying sizes co-existing with macro cells.

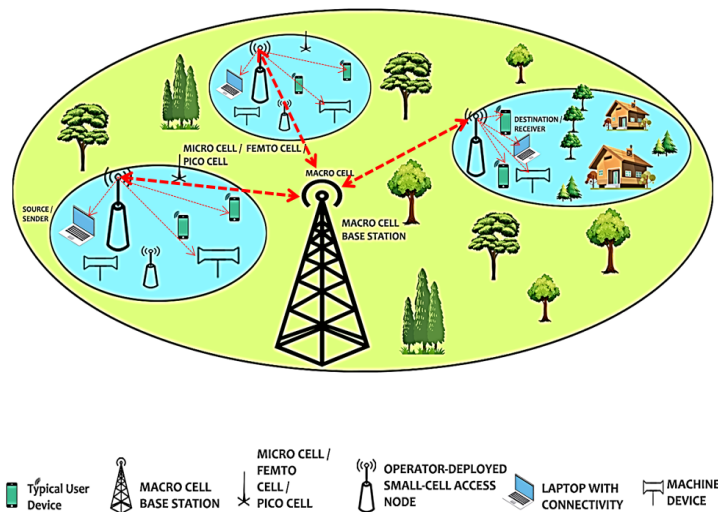


Figure 1 shows a generic UDN with mobile end users / relay nodes as source/destination pairs with deployment of large numbers of small cells of varying sizes including micro cell, femto cell, pico cell densify the network which co-exist and synchronize with the macro cells are shown.

The primary objective of routing protocols is to select a particular path out of a number of available paths and deliver packets from source to destination. The path for traffic movement can be within the same network or between/across multiple networks. These protocols play an important role to provide seamless connectivity and uninterrupted data communication and transfer between the source and the destination. Selection of an optimum routing protocol is a prerequisite for enhanced performance, reliability and service of the network. The traditional routing processes face several critical challenges in the formation of the routing paths. The process depends upon the type of network in use, the performance metrics and the channel characteristics (Shabbir et al., 2017).

Traditional routing in dynamic wireless networks has a lot of disadvantages and is a challenging issue revolving around many factors starting from network topology that change dynamically, network failures, constraints of resources, designing of routing protocol issues, unfavoured deployment conditions, etc. From the related literature, it has been observed that the as the size of the network grows exponentially, traditional approaches fail to provide the desired results and are more error prone and time-consuming (Kamel et al., 2016; Sharma et al., 2019).

Under such backdrops, lot of research has been done in recent times to search and form a feasible path between source and destination in dynamic environments. This will result in maximizing energy conservation of a network. The key criteria being considered is to design and create routing protocols which takes into account the critical issues of maximizing network lifetime and minimizing energy consumption. Of late, research has focussed on different nature inspired algorithms and met heuristics that imitate the nature for solving various optimization problems opening a new era in computational science. Different optimization techniques have been studied and used for the formation of low cost optimized paths among different available paths. Implementation of Swarm Intelligence (SI) based algorithms has led to the development of various routing protocols for dynamic dense networks. Thus, swarm based intelligent algorithms can be a potential substitute to provide the desired results for routing in dynamic Ultra Dense Networks (UDNs) (Aghbari et al., 2020).

There is a significant amount of work being reported which are related to dynamic and quality-aware routing in time-varying wireless networks. Also, dynamic routing policies have been suggested for multihop wireless networks subject to time-varying topology, random traffic and inter-channel interference. The proposed work uses only current condition of queue positions and channel condition requiring no prior knowledge of traffic and topology. In addition to throughput optimality, the work minimizes quadratic routing cost defined by providing each channel with a time-varying cost factor (Banirazi et al., 2020). In another performed work, the authors have proposed search region models based Markov chain and energy-efficient relays and an energy-efficient routing technique to further analyse the impact of state-transition probability (STP) with known residual energy on extending network lifetime of time-varying WSNs. Results show that the proposed algorithm can effectively extend network lifetime by considerable amount of time (Ding et al., 2021). But still there is ample scope for deriving optimized routing solutions in time-varying wireless networks by the use of hybrid PSO-GM solutions.

Frequent user mobility in dense networks results in their addition or disappearance in large numbers in such networks making the routing requirements fluctuate widely. Under such circumstances, time slots are considered with respect to the SPR problem in an UDN to predict the behaviour and calculate throughput requirements varying widely when deployed in build-up areas like railway stations, airports, bus terminals, metro terminals, etc. Further we can consider such a network configuring into different replicas with each variation of the time slots. Networking challenges developing in each of these time slots will require separate and unique routing solutions.

Further, traffic in the wireless networks are time dependent. The networks expand and shrink according to requirements which are also time dependent phenomena. As a result most of the behaviour and parameters of such networks demonstrate a strong time dependent aspect. Data traffic generated by Machine Type Communication (MTC) devices in 5G networks may be either periodic in nature or event-triggered which means it will exhibit time dependent behaviour. Also, it is impossible to model data traffic due to non-stationary time dependent behaviour of traffic generated by each type of service. In the performed work, special correlation functions of stochastic point processes called Product Densities (PDs) are applied for estimating traffic under non-stationary time dependent arrival rates. For Human Type Communication (HTC), PDs are defined for estimating time-dependent offered load of connection-level service requests. For MTC, PDs are defined at any given instant of time for estimating the number of devices connected to the base station (BS) (Chetlapalli et al., 2020). Also, the authors have proposed a performance modelling technique for studying the time fluctuating network layer behaviour of multihop wireless networks based on queuing with constant data bit rate traffic. Here a hybrid model of fluid flow queuing technique and a time fluctuating connectivity matrix has been presented (Xu et al., 2010).

In view of the above, the routing challenges of the UDNs become a critical issue dependent on time varying behaviour. The routing issues needs optimized solutions many of which can be nature inspired. The primary advantage of such approaches is related to the fact that provide ample of opportunities to conserve resources. Difficulties in Network Management in communications are

increasing by the day. This is due to rapidly changing topology of networks with time, the increasing size of networks and complexity. Thus, a new set of algorithms inspired by swarm intelligence (SI), is currently being investigated and developed that can solve numerous problems of such type networks which are dependent on time varying characteristics (Gui et al., 2016).

In our proposed work, the shortest optimal route of the source/destination pair is found using a set of evolutionary optimization algorithms namely Particle Swarm Optimization (PSO) Algorithm, Genetic Algorithm (GA) and our proposed hybrid Particle Swarm Optimization–Genetic Mutation (PSO-GM) algorithm which searches for optimized solution by representing it as a SPR problem. The key attribute of the Genetic Mutation (GM) approach is related to the application of the five mutation techniques adopted to determine the optimized shortest path search. The GM is performed using an amalgamated strategy evolutionary programming algorithm (ASEPA) with Gaussian, Cauchy, Levy, Single-point and Chaos mutation operators.

The rest of the paper is organized as follows. In the Proposed Work Section, we cover the details of the proposed algorithms for the SPR problem and the details of the work done. In Experimental Results Section, we include all the experimental details and the results derived. The paper concludes with a summary in Conclusion Section.

PROPOSED WORK

In this section, we cover the details of the proposed algorithms for the SPR problem and the details of the work carried out. First, we discuss the application of our proposed PSO for the SPR in Ultra Dense Networks. Next, we report the use of our proposed GA for solving the routing problem in the UDNs. Finally we include the details of the application of our novel time slot based PSO-GM approach which is developed by extracting the best possible features of the above two mentioned protocols and integration of few additional features. Further, we use the convergence rate with epochs of the evolutionary techniques to justify their state of deployment in the UDNs and Route Success Ratio (RSR) for ascertaining the performance of the methods in the UDN set-up. Moreover, as already discussed, the details of the hybrid Particle Swarm Optimization–Genetic Mutation (PSO-GM) algorithm formulated for optimized SPR is also discussed. The GM is an amalgamated strategy of evolutionary methods with Gaussian, Cauchy, Levy, Single-point and Chaos mutation operators.

UDNs are described as networks where the count of cells exceeds the number of active users (López-Pérez et al., 2015). It is expressed as

$$\lambda_a \gg \lambda_u \quad (1)$$

where λ_a is the access point density and λ_u is the count of active user density. Ding et al. have presented an additional countable measure of the density at which a network can be considered heterogeneously ultra-dense (> 1000 cells/km²). In fact, both the descriptions overlap with one another which implies that the active users density in dense urban environments is maximum bounded to about 600 active users/km² (Ding et al., 2015).

A. Proposed PSO For The SPR Problem In The UDN

Kennedy and Eberhart developed and proposed the PSO computational technique in 1995 (Lindfield et al., 2017). From the literature we have found that the PSO algorithm has been applied extensively to provide optimal solutions to SPR problem in wireless networks (Mohammed et al., 2008). The PSO proposed in our work consists of a search space where each candidate or particle of the initial random population holds its own fitness value. The fitness value is computed based on the value

returned by the objective function. After the end of the iteration, the movement of the particle is computed by the following equations

$$x_i(t+1) \leftarrow x_i(t) + v_i(t) \quad (2)$$

$$v_i(t+1) \leftarrow \omega v_i(t) + c_1 r_1 (pbest_i(t) - x_i(t)) + c_2 r_2 (gbest_i(t) - x_i(t)) \quad (3)$$

Eq. (2) represents the position of particle i at time t and is denoted by $x_i(t)$. Eq. (3) represents the velocity of particle i at time t and is denoted by $v_i(t)$. $pbest_i(t)$ is the current best position found by the particle itself until now and also called the personal-best value. Also, $gbest_i(t)$ is the best position found by the whole swarm until now and ω is an inertia weight scaling the previous time step velocity. Also, c_1 and c_2 are the two acceleration coefficients, scale the influence of the personal best position ($pbest_i(t)$) and the global best position ($gbest_i(t)$). Random variables r_1 and r_2 are within the range of 0 and 1.

B. Proposed GA for The SPR Problem In The UDN

GA is one of the most popular biologically inspired and stochastic global optimization algorithms. It is used to find optimal solutions to varied global optimization problems inspired by the biological theory of evolution by means of natural selection (Lindfield et al., 2017). We have found in the reviewed literature that the GA algorithm has been applied extensively to provide optimal solutions to the SPR problem. Ahn et al presented a modified GA with priority on the population size of the candidate solutions to formulate the SPR problem (Ahn et al., 2002). Roshani et al. have proposed a parallel genetic algorithm as a potential solution to the SPR problem. The discussed algorithm reduces computation time by distributing load balance between multiple processors. Fine-Grained GA model is applied and the proposed algorithm was simulated on Wraparound Mesh network topologies of different sizes and scales. Simulation results displayed optimal performance and improvement of timing germane shortest path routing (Roshani et al., 2015).

Here we report the use of GA based approach for SPR in UDNs. The proposed GA consists of an initial random population. The population comprises of both feasible and infeasible solutions also known as chromosomes. The chromosomes are of variable length in order to make the algorithm more accurate and increase the area of the search space.

Fitness Function- The chromosome represents the path cost which is used to calculate its fitness. The defined fitness function is

$$f_i = \frac{1}{\sum_{j=1}^{L_i-1} C_{g_i(j), g_i(j+1)}} \quad (4)$$

In the above equation (4), the fitness score of the i -th chromosome is denoted by f_i . The length of the i -th chromosome is denoted by L_i . Here $g_i(j)$ represents the gene or node of the j -th locus in the i -th chromosome. Also, C is the link cost between the nodes (Ahn et al., 2002).

C. Proposed Hybrid PSO-GM For The SPR Problem In The UDN

Review of the literature related to performance analysis of the PSO and GA gives us the conclusion that each one has its own advantages and disadvantages based on their application to different global optimization problems. Stagnation and early convergence problem of the PSO has also been discussed (Lindfield et al., 2017). The reviewed literature has given us the understanding that as the size of the network grows or shrinks in a dense surrounding, the efficiency and accuracy of the computed results through the mentioned protocols can be compromised to an extent. Consequently related research developed and concentrated on combining PSO with other evolutionary search algorithms such as GA (Ercan et al., 2013), Genetic Programming (Qi et al., 2013), Ant Colony Optimization (Li et al., 2013) and ABC (Kiran et al., 2013) etc. to maintain the diversity of the population.

Jordehi proposed a new variant PSO called as Enhanced Leader PSO (ELPSO) for minimizing the premature convergence problem. The algorithm is based on a successive five-stage mutation scheme applied to the global best leader including Gaussian, Cauchy, opposition based mutation on dimensions and the global best as a whole and mutation based on Differential Evolution (DE) to increase its diversity. Their experimental results prove the scalability and accuracy of the algorithm (Jordehi; 2015). Sun et al. proposed a cooperative PSO with two swarms namely the master and slave swarms in order to achieve optimum balance between swarm diversity and convergence speed. Slave swarm particles update themselves by learning from the neighbor particles whereas master swarm particles update themselves based on the slave swarm particles with bigger inertia weight (Sun et al., 2014). Chang also proposed a modified PSO with numerous subpopulations for optimization of multimodal functions. The fittest particle of each sub population will likely replace the global best candidate generated by the original PSO and direct the search towards optimum solutions (Chang; 2015).

Zhang et al. have proposed a hybrid PSO algorithm which handles premature convergence and local optimum trap as compared to conventional PSO which exhibits limitations in doing so. The proposed algorithm combines PSO with GA and mutation techniques to achieve population diversity and convergence speed. The algorithm employs the sub-swarm concept and cooperative mechanisms to enable mutation of each sub-swarm and direct the search towards a global optimum solution (Zhang et al., 2015).

From the related works, we have studied and analyzed different techniques which search for optimized solutions to the SPR problem in networks. Abdel-Kader proposed a novel QoS multicast routing scheme with bandwidth and delay constraints. The proposed scheme applies the discrete PSO algorithm to the search space for the optimal multicast tree satisfying the QoS parameters which is one type of SPR problem. A novel PSO-GA hybrid routing algorithm was proposed which combines PSO with genetic operators and applied to provide optimum search results of the solution space. Simulation results show that the proposed algorithm provide better and accurate results to the routing problem (Abdel-Kader; 2011). Saraswati et al. proposed an intelligent hybrid PSO-GA algorithm for Wireless Mesh Networks (WMN) to solve the routing problem which satisfies the QoS requirements and integrates the advantages of PSO and GA. Simulations results prove that the hybrid approach has better convergence results compared to PSO and GA applied individually (Saraswati et al., 2015). Considering the reported works and the scope for further improvement, we have proposed a novel time slot based hybrid PSO-GM to compute an optimal solution to the SPR problem in a dense network. Although there is considerable work being done on time varying network solutions, there is further scope for deriving such solutions by the use of hybrid PSO-GM solutions (Banirazi et al., 2020; Ding et al., 2021; GUI Et Al., 2016).

Our proposed hybrid PSO-GM algorithm repeats and considers time slots t_i where $i = 1, 2, 3 \dots n$ and time dependent replicas of network $N(t_i)$. We also consider multiple sources S_i to multiple destinations D_i pairs, where any node n_j in the network represents S_i and D_i and $j=1, 2, 3 \dots N$ and apply our hybrid PSO-GM. For particles P_i where $i = 1$ to p in population P , the algorithm initializes

the position and velocity of each particle in the population. Repeating for each particle in the overall population, it performs a conventional PSO operation. Here, P_i is evaluated by defined PSO fitness function and updates the position and velocity of each particle. It then calculates the individual best particle value p_best and global best particle g_best in population P_i .

Next, the overall population is divided into two subpopulations, $pop1$ and $pop2$. From the first subpopulation, $pop1$, two best leaders $L1$ and $L2$ are selected based on their fitness values and are utilized as parents for the GA to produce offspring. If the fitness value of the mutated offspring is better, then it will replace the weaker parent. The process continues until the fittest offspring P_{G_pop1} is finally selected as the new leader of the subpopulation $pop1$. The results reveal that the GA process allows short jumps to the leader to escape stagnation from local optimum trap and also introduces diversity to the subpopulation and helps to avoid premature convergence.

Similarly, from the second subpopulation, $pop2$, the leader P_{G_pop2} is selected based on the returned fitness values and subsequently a series mutations are applied to this sub-swarm leader through our proposed amalgamated strategy evolutionary programming algorithm (ASEPA) which is discussed below. The mutation techniques that are applied include the Gaussian, Cauchy, Levy, Single-point probability and Chaos distributions as mutation operators (Dong et al., 2005).

The main advantage of our PSO-GM approach is that the GA and the five mutation operations work collaboratively to prevent early convergence. Further, in the work continues in background and foreground mode where all the mutations operate in separate streams to find the optimal solution. In an event when particular optimization iteration is unable to update further, the operator which can carry on the mutation comes into action and carries forward the process. For instance in a run, if the GA process gets confined to a local optimum and is not able to produce a fitter offspring for $pop1$, the mutation techniques take over control and promotes long jumps from the previous best solution in $pop2$ to reduce the chances of premature convergence. On the other hand, if the mutation operations falter, the GA extends support and expands the search space by employing crossover, mutation and replace functions to augment the sub-swarm $pop1$ and then the overall population. The principle behind this amalgamated strategy is to continue the search for optimized SPR despite local fluctuations and restrictions. The collaboration logic for the proposed hybrid PSO-GM has been shown in Figure 2.

Evolutionary Programming proposes several mutation operators but these operators individually cannot efficiently solve all types of global optimization problems. Therefore, an amalgamated strategy which is the combination of multiple mutation operators will be able to outplay the flaws of a pure strategy which is nothing but an individual mutation operator. The idea is to select the optimal mutation operator out of the available ones for each generation and use it to produce fitter solutions which will definitely yield better results than a pure strategy.

The Gaussian and Cauchy mutation processes displays significant amount of flexibility for exploration and exploitation along the search. Levy and Single point distribution applies adjustable parameters to assist and design mutation operators to perform longer jumps. Chaos mutation also helps to prevent premature convergence, generates faster convergence speed and diversifies the population. Compared to the conventional GA, this amalgamated strategy promotes longer jumps to avoid confinement to local optimum solutions and find global optimum, facilitates better exploration of the search space, increases diversity to the swarm leader and helps to avoid stagnation (Zhang et al., 2015).

AMALGAMATED STRATEGY EVOLUTIONARY PROGRAMMING ALGORITHM (ASEPA) FRAMEWORK

In this paper, we have proposed the ASEPA based approach motivated by evolutionary game theory (Sandholm; 2020). As already discussed, the ASEPA aims to combine the five different mutation operators namely the Gaussian, Cauchy, Levy, Single-point probability and Chaos. In ASEPA, at

each generation the fittest individual or the sub-swarm leader P_{G_pop2} chooses one of the five mutation strategies with probability 0.20 and according a definite probability distribution to generate offspring or mutated leader. The distribution is fine-tuned dynamically based on the mutation strategy performance.

In terms of game theory, a single mutation operator is known as a pure strategy. The set or vector of pure strategies used by all the individuals is called as a pure strategy profile and is denoted by $\vec{s} = (s_1, \dots, s_n)$ where s_i the pure strategy is used by individual i in the population.

At each generation, a mutation operator is selected from its strategy set by each individual based on a definite probability distribution. The distribution over the set of pure strategies available to an individual is known as a mixed strategy of individual i . The mixed strategy set or vector is denoted by $\vec{ms}_i = (ms_i(1), \dots, ms_i(m))$ where m is the number of strategies and $ms_i(h)$ is the probability that individual i applies pure strategy h for mutation.

The ASEPA will apply a mixed mutation strategy consisting of three phases.

1. Mutation: Phase that will introduce diversity or variety to the individuals.
2. Selection: Phase that will prioritize certain individuals over others.
3. Updation: In this phase, the sub-swarm leader will apply and fine tune its mixed strategy based on the payoff of the pure strategies. Each of the operators has an additional decision making mechanism which applies the principles of soft voting and hard voting. They will contribute in their individual capacity and vote to find the global optimal solution.

Mutation: For sub population pop2, at each generation, the sub-swarm leader P_{G_pop2} selects a mutation operator with probability 0.20 from its strategy set in accordance with its mixed strategy and undergoes a series of mutations to produce new mutated leaders in the form of offspring. The strategy set is a combination of the following five mutation operators.

Gaussian Mutation: The Gaussian distribution that is applied to mutate the sub-swarm leader uses the following equation (Jordehi;2015)

$$P_{G1_pop2}(d) = P_{G_pop2}(d) + (X_d^{max} - X_d^{min}) \times \text{Gaussian}(o, h) \text{ for } d=1, 2 \dots n \quad (5)$$

where *Gaussian* (o, h) is the Gaussian distribution, o is the mean of the distribution with h as the standard deviation which decreases linearly with execution. X_d^{max} and X_d^{min} are the upper and lower bounds of the decision vectors in the d -th dimension, P_{G1_pop2} is the new mutated leader and replaces the old swarm leader P_{G_pop2} when the fitness value of P_{G1_pop2} is greater than P_{G_pop2} .

- (b) **Cauchy Mutation:** The Cauchy distribution that is applied to mutate the sub-swarm leader uses the following equation (Jordehi;2015)

$$P_{G2_pop2}(d) = P_{G_pop2}(d) + (X_d^{max} - X_d^{min}) \times \text{Cauchy}(g, s) \text{ for } d=1, 2 \dots n \quad (6)$$

where *Cauchy* (g, s) denotes Cauchy distribution and g is the location of the peak and s is the scale parameter of the distribution which decreases linearly during the run, P_{G2_pop2} is the new

mutated leader and replaces the old swarm leader P_{G_pop2} when the fitness value of P_{G2_pop2} is greater than P_{G_pop2} .

(c) Levy Mutation: The Levy distribution can be derived from Fourier transform as

$$L(\mu, k, \eta) = e^{-\mu|k|^\eta} \quad (7)$$

where μ is the scale factor which ranges from -1 to 1 and η is the Levy index which ranges from 0 to 2. Thus, Levy mutation is applied to mutate the sub-swarm leader as

$$P_{G3_pop2}(d) = P_{G_pop2}(d) + (X_d^{max} - X_d^{min}) \times L(\mu, k, \eta) \quad (8)$$

where $L(\mu, k, \eta)$ denotes Levy distribution (Hakli et al., 2013), P_{G3_pop2} is the new mutated leader and replaces the old swarm leader P_{G_pop2} when the fitness value of P_{G3_pop2} is greater than P_{G_pop2} .

(d) Single Point Mutation: Only one component of the total n components is mutated in each run. The Single Point mutation is applied to the sub-swarm leader as

$$P_{G4_pop2}(d) = P_{G_pop2}(d) + (X_d^{max} - X_d^{min}) \times N_j(0, 1) \text{ where } j=1, 2 \dots m \quad (9)$$

where $N_j(0, 1)$ represents Single Point Mutation (Dong et al., 2005), P_{G4_pop2} is the new mutated leader and replaces the old swarm leader P_{G_pop2} when the fitness value of P_{G4_pop2} is greater than P_{G_pop2} .

(e) Chaos Mutation: Here, the Logistic function also called as Chaotic Function is used as a mutation operator which is given by the logistic equation

$$C_{l+1} = \lambda C_l (1 - C_l), \quad C_l \in [0, 1] \text{ where } \lambda=4, l=1, 2, \dots, W. \quad (10)$$

The Chaotic mutation is applied to the sub-swarm leader as

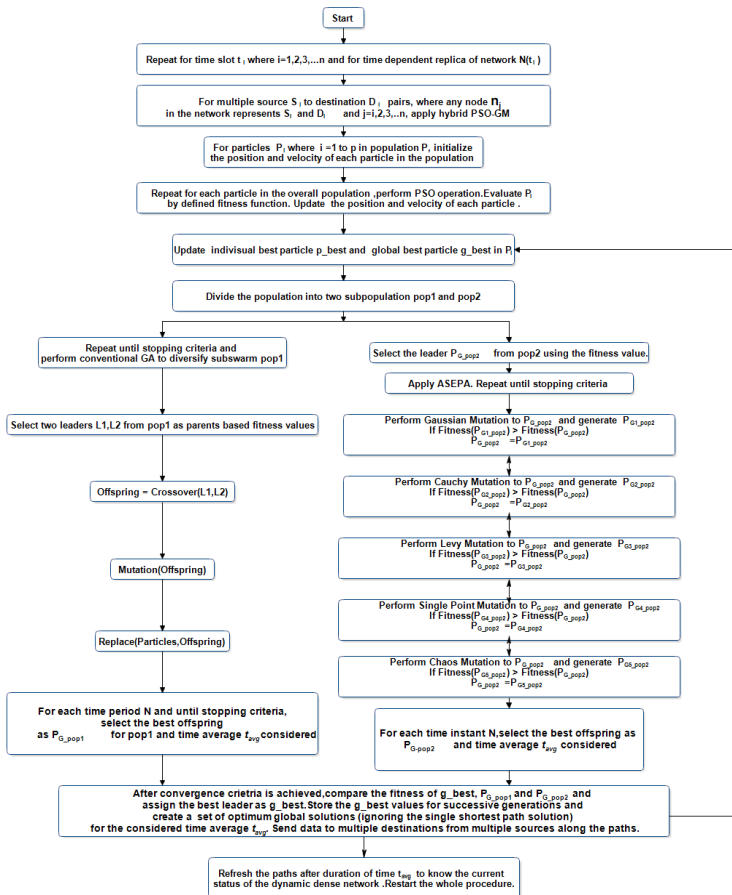
$$P_{G5_pop2}(d) = P_{G_pop2}(d) + (X_d^{max} - X_d^{min}) \times C_j(0, 1) \text{ where } j=1, 2, \dots, m \quad (11)$$

where $C_j(0, 1)$ is a new random generated for each individual j from the Chaotic Function with parameter λ (Dong et al., 2005). P_{G5_pop2} is the new mutated leader and replaces the old swarm leader P_{G_pop2} when the fitness value of P_{G5_pop2} is greater than P_{G_pop2} .

Selection: In this phase, we will prioritize certain individuals over others which are same as that used in traditional Evolutionary Programming (EP). Fitness value is assigned to the new mutated leader and then compared with the original sub-swarm leader. The one with the higher fitness value is then selected as the new leader of the sub-swarm.

Updation: In this phase, the sub-swarm leader will apply and fine tune its mixed strategy based on the payoff of the pure strategies. Normally, the strategy s_i with a better payoff will be chosen with a higher probability in the next course of action to determine the new mixed strategy. For example, if the new mutated leader from Gaussian mutation P_{G1_pop2} is able to replace the old leader P_{G_pop2} then it will be assigned a positive payoff because this pure strategy was successful in generating a fitter offspring or new leader. Otherwise it will be assigned a negative payoff. Each of the operators has an additional decision making mechanism which applies the principles of soft voting and hard voting. They will contribute in their individual capacity and vote to find the global optimal solution. The idea is to combine conceptually different mutation operators and use the average predicted probabilities (soft vote) or a majority vote (hard vote) to obtain the best optimal solutions. Both soft voting and hard voting have been used since many real world phenomenon demands use of both these mechanisms in a combined manner. Such a mechanism

Figure 2. Flowchart of the hybrid PSO-GM Algorithm



called the Voting based Best-Selection Decision can be useful for a set of equally well performing model of operators in order to balance out their individual weaknesses.

- (a) **Weighted Average Probabilities (Soft Voting):** In soft voting, the predicted value for a particular solution is based on the weighted average probabilities of the operators. Specific weights are being assigned to each mutation operator. When weights are provided, the predicted probabilities for each operator are collected, multiplied by the operator weight, and averaged. Based on these weighted average probabilities, we can then select the optimal solution from the operators voting for a solution with highest average. To illustrate this with a simple example, let's assume we have the five mentioned mutation operators and a 3-class solution optimization problem

where we assign equal weights to all operators (default): $w_1=1, w_2=1, w_3=1, w_4=1, w_5=1$. The weighted average probabilities for the solution would then be calculated as discussed below.

Table 1. Weighted average probabilities (soft voting)

Operators	Solution1	Solution 2	Solution 3
Gaussian	$W1*0.2$	$W1*0.5$	$W1*0.3$
Cauchy	$W2*0.6$	$W2*0.3$	$W2*0.1$
Levy	$W3*0.3$	$W3*0.4$	$W4*0.3$
Single-Point	$W4*0.2$	$W4*0.4$	$W4*0.4$
Chaos	$W5*0.3$	$W5*0.4$	$W5*0.3$
Weighted Average	0.32	0.40	0.28

The contribution of the five mutation operators in selecting the best solution to the SPR problem is shown in Table I. Here, the operators have voted for Solution 2 with the highest weighted average and hence is being selected.

Next, our aim is to find optimal weights as against constant weights in order to increase the prediction accuracy. In order to achieve this, we have used the Gradient Descent Algorithm (Ruder; 2016) to modify/update the weights in each run and calculate new weights W^+ from our current weights W using

$$W^+ = W - \eta \tilde{N}C \quad (12)$$

In the eq. 12, η is a constant called the learning rate and C is the cost function. The learning rate denotes the amount the gradient vector will be used to update the current set of weights into new ones. If a very small value for the constant is chosen, the weights adjust very slowly and converge to a local minimum in a long time. On the other hand, if the learning rate is set too high it might overpass or display a non-convergent behavior. $\tilde{N}C$ is the gradient of the cost function with respect to the weights. In other words, how much the cost function C changes when the weights changes. Expanding eq. 12

$$\begin{bmatrix} W_1^+ \\ W_2^+ \\ \dots \\ W_n^+ \end{bmatrix} = \begin{bmatrix} W_1 \\ W_2 \\ \dots \\ W_n \end{bmatrix} - \eta \begin{bmatrix} \frac{C}{W_1} \\ \frac{C}{W_2} \\ \dots \\ \frac{C}{W_n} \end{bmatrix} \quad (13)$$

- (b) Majority Voting (Hard voting): In majority voting, the predicted value for a particular solution is the value that simply takes the majority of the predictions into account provided by each of the individual operators. For a given solution S2, if we get votes from M different operators, the majority voting will assign the result which has been voted by majority of the operators.

Table 2. Majority voting (hard voting)

Operators	Solution1	Solution 2	Solution 3
Gaussian	0	1	0
Cauchy	0	1	0
Levy	1	0	0
Single-Point	0	0	1
Chaos	0	1	0

As shown in Table 2, the voted value for a solution is represented by 1 and 0 otherwise. The operators voted for Solution 2 with majority of 3 (voted by Gaussian, Cauchy and Levy) and hence the predicted/selected value is Solution 2. In case of a tie, the majority voting will predict/select the solution from any of the equal choices.

The above process continues for certain fixed number of time windows and the average performance out of different accounted time slots are used to find the average value. The average performance of the operators forms the basis of optimization cycles used for determining the shortest routes among the source destination pairs. The process continues under varying load conditions and the performances are monitored and compared to average or previously obtained best results. It continues iteratively and philosophically follows the survival of the fittest paradigm.

In our work, a copy of the g_best value obtained initially from conventional PSO process is stored. It is then compared with the new two best optimal values of the subpopulations (pop1, pop2) obtained from conventional GA and the Amalgamated Strategy Evolutionary Programming Algorithm (ASEPA). It is then used to compute the fittest leader of the entire population designated as g_best among the three which is the leader to lead the swarm. The entire process executes until the termination criteria is reached. The g_best values for successive generations are maintained and a set of optimum global solutions is created ignoring the single shortest path solution for the considered time average t_{avg} . The set of multiple optimal solutions has been created since we have considered multiple source/destination pairs in our replica of a dense network. Concurrent data transmission takes place to multiple destinations from multiple sources along the paths. Refresh the paths after duration of time t_{avg} to know the current status of the dynamic dense network and restart the whole procedure. The flow chart for the proposed hybrid PSO-GM has been shown in Figure 2.

Mean Squared Error: Mean Squared Error (MSE) is a very commonly used general purpose error metric for numerical predictions. It is a well-known model evaluation metric more frequently used with regression models. The MSE of a model with respect to a test set is the mean of the square of all the errors over all instances in the test set. The prediction error is defined as the difference between the true value and the predicted value for an instance

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n \left(y_i - \lambda(x_i) \right)^2 \quad (14)$$

where y_i represents the true target value for test instance x_i . $\lambda(x_i)$ represents the predicted target value for the test instance x_i and n is the number of test instances.

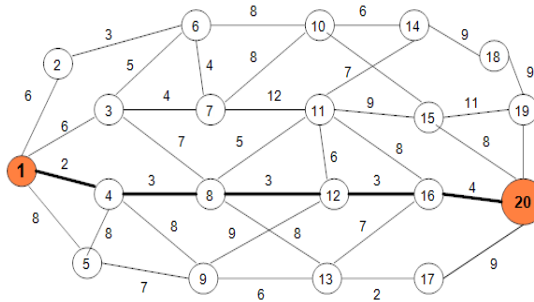
EXPERIMENTAL RESULTS

In our performed experimental work, all computer simulations have been performed in MATLAB 18 software environment representing an UDN consisting of 20 to 2000 nodes under several time windows. The mutation probability parameter is set to 0.05 in all the experiments. The implemented algorithms are PSO, GA and our hybrid PSO-GM which is individually applied to find shortest path based on minimum cost (derived from the fitness function) from source to destination to solve the SPR problem. Each run of the simulation is terminated when all the solutions or chromosomes have converged to a defined and dedicated solution. Dijkstra's solution is chosen as an algorithm of reference for benchmarking purpose. Each feasible solution is compared with it to verify its accuracy and validity. The simulation parameters are listed in Table 3.

Table 3. Simulation parameters

Parameter	Value
Routing Protocols	PSO, GA and hybrid PSO-GM
Area	1000 *1000 square meter
Simulation Time	900 sec
Network Type	Wireless Network
Packet Size	512 bytes
Data Traffic	CBR (UDP)
Bandwidth	6 Mbps
Transmission Rate	4 packets /sec to 4000 packets /sec
Maximum Speed	20-80 m/s
Number of Nodes	20,25,50,75,100,125, 130, 140 and 150
Number of Connections	4, 8,12 and 16 connections
Pause Time	0, 300, 600 and 900
Packet Generation Rate	4, 6, 8, 12 and 16 packets/sec
Transmission Range	250 m

Figure 3. Display of simulation results for the paths found by Dijkstra's shortest path, GA, PSO and our novel hybrid PSO-GM approach.



Simulation Results for a Fixed Network with 20 Nodes:

In the beginning, we have considered a 20 node UDN for our research and study. Subsequently, we have extended our work on different network types and scales with nodes expanding up to 1200 in one slot and up to 2000 in another to converge with our idea of a Heterogeneous Dense Network. A total of 300 network topologies have been considered and performances noted.

Figure 3 shows that the application of each of the four algorithms return a similar total cost of 15 and the path is being highlighted by bold lines from Source Node 1 to Destination Node 20. The size of the population is equal to the number of nodes in the network so that we can have a fair comparison of the performance and competence of the algorithms. The path computed by the proposed algorithms converges with the one computed by Dijkstra's algorithm, which is one of the most established algorithms for solving the SPR problem (Ortega-Arranz et al., 2014). The results justify the authenticity and accuracy of the algorithms in finding optimal solutions to the SPR problem.

Figure 4. Convergence Property of PSO, GA and the hybrid PSO-GM w.r.t Dijkstra's algorithm.

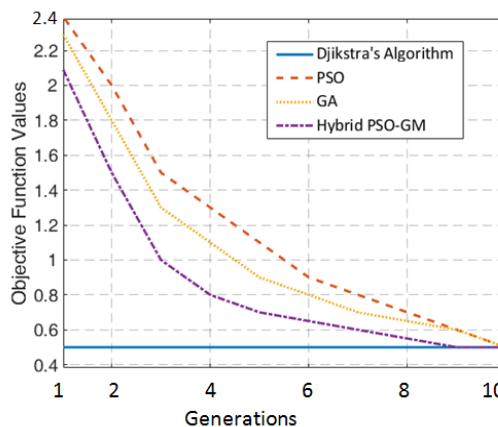


Figure 4 illustrates the comparison of the objective-function values of all the four proposed algorithms against the number of iterations. From the figure we can see that our hybrid PSO-GM has

the fastest rate of convergence to the theoretical limit which is determined by the Dijkstra's algorithm. This is because it takes the least number of iterations to converge with Dijkstra's algorithm whose value is always constant. The advantages of PSO, GA and GM combine together to carry out this work and generate this path convergence.

We have extended our research and investigated UDNs of 25-150 relays nodes with source/destination pairs and normalized link costs metric. A total of 300 network topologies have been considered in each case. Firstly, we have investigated the route optimality (quality of solution) for each proposed algorithm. The route optimality is the percentage of the number of times that the proposed algorithm finds the global optimum or the shortest path of the source/destination pair.

Yu et al. have done a space-time analysis of inbound and outbound passengers of Nanjing metro and have shown the 24-hour fluctuation of daily average passenger flow with different criteria. In our experimental work, we have replicated this metro station as a 5G dense network with majority of passengers having access to mobile nodes and high bandwidth requirements to send/receive large amounts of data from multiple source/destination pairs for multiple applications running in their nodes. Daily data are counted to 24 hours, 0-23 o'clock and time data is accurately calculated to seconds. The normal

Figure 5. Comparison of Route Success Ratio (RSR) values for each algorithm in 4 time slots T1, T2, T3 and T4.

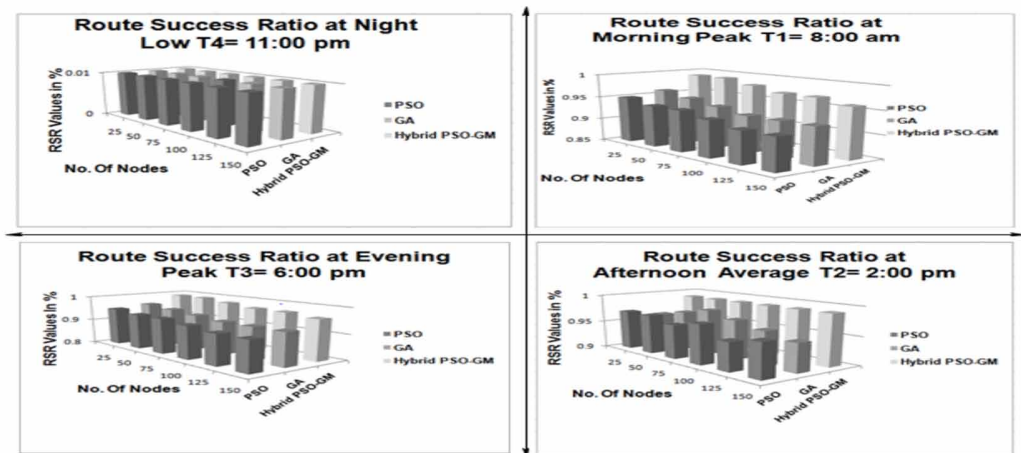


Figure 6. Probability Density Function Values against time slots.

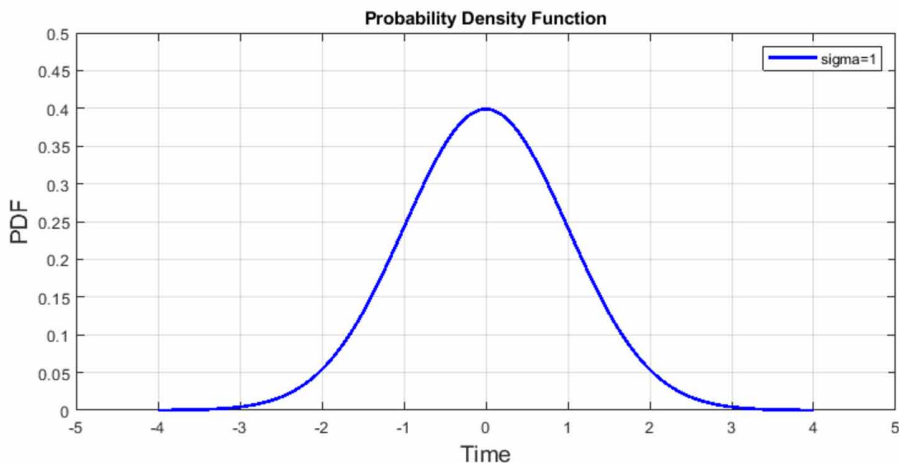


Table 4. Performance of the 5 operators in varying load conditions

SLNO	Time Slots	Load Condition	Avg Accuracy in %	
1	T1	Max	Gaussian	95
			Cauchy	96
			Levy	97
			Single-Point	93
			Chaos	92
		Min	Gaussian	97
			Cauchy	98
			Levy	99
			Single-Point	94
			Chaos	93
2	T2	Max	Gaussian	96
			Cauchy	97
			Levy	98
			Single-Point	94
			Chaos	93
		Min	Gaussian	97
			Cauchy	97
			Levy	98
			Single-Point	95
			Chaos	94
3	T3	Max	Gaussian	95
			Cauchy	96
			Levy	97
			Single-Point	93
			Chaos	92
		Min	Gaussian	97
			Cauchy	98
			Levy	99
			Single-Point	94
			Chaos	93
4	T4	Max	Gaussian	99
			Cauchy	99
			Levy	99
			Single-Point	98
			Chaos	97
		Min	Gaussian	99
			Cauchy	99
			Levy	99
			Single-Point	98
			Chaos	97

working hours in the city are from 9:00 am to 5:00 pm. The total duration of 24 hours is broken down into four slots with the first slot beginning at 6:00 in the morning and reaching the peak at 8:00 am as the passengers leave and arrive for work. Subsequently, the passenger flow begins to decline during day time and has an average flow during the day period. Gradually the passenger flow reaches another peak in the evening at 6:00 pm as the offices are closed. Again the number of passengers begins to decline and between 11:00 pm and 6:00 am, there are almost no passengers (Yu et al., 2019).

We have considered these four 6-hour time periods and have taken instantaneous time values in these slots to show the route success ratio calculations and variations in these time intervals. Figure 5 illustrates the route optimality of all the proposed algorithms in the four considered time periods, namely T1 as Morning Peak, T2 as Afternoon Average, T3 as Evening Peak and T4 as Night Low. From the figure, we can see that the overall route success ratio of our proposed hybrid PSO-GM is much higher than the other two algorithms at T1, T2, T3 time periods irrespective of the number of nodes ranging from 25 to 150. For instance at Morning Peak time period T1, the hybrid algorithm has a optimal route success ratio of almost around 99% at 25 nodes which slowly decreases as the number of nodes keeps on increasing to 150. The Evening Peak time period T3 also generates similar results. In the Afternoon Average time period T2, the hybrid algorithm also displays optimal performance. Only in the Night Low time period T4, all the three algorithms gives similar performance since there are almost no users with data traffic requirements. The data sets that are generated by the computed mean, standard deviation and probability density function (pdf) are found to closely approximate a Gaussian Normal Distribution which is shown by the graph plot in Figure 6.

For a sizeable number of time slots where $T=500$, we have checked the performance of the five operators in varying load conditions in the replicated Nanjing Metro. We are summarizing mean values of the five operators that have been shown in Table3 and have again considered the four time slots T1, T2, T3 and T4 in the 24-hour zone of the Nanjing Metro.

From the literature, we have found that the Gaussian mutation operator is the classical mutation used in Conventional Evolutionary Programming (CEP) but it is inefficient in solving multi-modal functions. Cauchy distribution based mutation operator was proposed as Fast Evolutionary Programming (FEP) which converges faster to an optimal solution than Conventional EP for multivariate functions. Also, Cauchy mutated offspring comes with more diversity compared to parents. Levy distribution is more flexible than CEP and FEP. It applies adjustable parameters to assist and design mutation operators to perform longer jumps which increase the search space area for optimal solutions to the SPR problem. LEP is similar to FEP when its scaling parameter β is equal to 1 and similar to CEP when β is set to 2 (Lee et al., 2004). The Single Point mutation operator searches for only one component of the solution in each generation thereby limiting its applicability to solve the SPR problem. The Chaos mutation operator also has a limited search space area and does not promote longer jumps due to its single logistics or chaotic function.

We have used the five operators in all our simulated scenarios and have generated path solutions in the UDN. We have computed the shortest path routing solutions using all the mentioned operators in varying load conditions in the UDNs. Further we have compared the performance with the standard Dijkstra's algorithm under static conditions by which we mean the performance derived in different limits of maximum and minimum load conditions denoted by Max and Min in fixed size UDN's. In time slot t1 which represents the morning peak, the Levy operator has an average accuracy of 97% and 99% under Max and Min load conditions. In time slot t2, the day time average period the Levy operator has an average accuracy of 98% in both Max and Min conditions. The performance of the operators in time slot t3 in the evening peak is almost same as that of time slot t1 with the Levy operator registering an accuracy of 97% and 99% respectively. Lastly in time slot t4, where there are almost no end users the Gaussian, Cauchy and Levy operators have a similar accuracy of 99% in both Max and Min varying load conditions. Single Point and Chaos is slightly behind with 98% and 97% accuracy in both Max and Min conditions.

Figure 7. Global Optimum Solution Percentage of Hybrid PSO-GM against different number of Nodes.

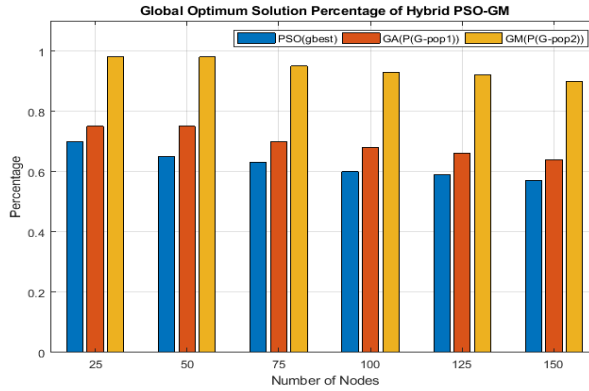
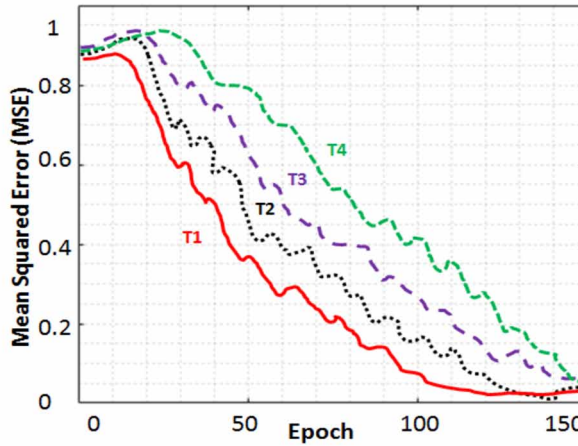


Figure 8. Mean Squared Error (MSE) versus Epoch for the 4 time slots T1,T2,T3,T4.



. As already mentioned this approach generates three leaders or solutions in one complete execution. So, we have simulated and analyzed the results of the three leaders obtained from our novel hybrid PSO-GM approach against different number of nodes. First one designated as the g_best obtained initially from conventional PSO process and then the new two best optimal values of the subpopulations (pop1, pop2). The one obtained from conventional GA in subpopulation pop1 is denoted as P_{G_pop1} and the Amalgamated Strategy Evolutionary Programming Algorithm (ASEPA) in subpopulation pop2 as P_{G_pop2} . These three are then compared against each other to compute the fittest leader of the entire population designated as g_best which is the global optimum solution. Figure 7 illustrates the global optimum solution percentage of Hybrid PSO-GM approach. The results displayed in the figure indicate that P_{G_pop2} obtained from the ASEPA in subpopulation pop2 provides

the highest percentage of success ratio in generating the global optimum solutions to the SPR problem in UDNs.

We have calculated the MSE related to the working of the proposed hybrid PSO-GM model with Dijkstra's Algorithm as the benchmark. The benchmark algorithm's static condition performance is shown against the MSE convergence under dynamic state associated with the PSO-GM approach. This is shown in Figure 8. The MSE of the four different time windows in which the PSO-GM deals with the SPR shows convergence to optimal value as epochs increase. It indicates that SPR generated by the PSO-GM in four different traffic conditions provide optimal solutions. Around 150 epochs, in all the four different load conditions, the PSO-GM performs to minimize error and produces routing solutions under dynamic conditions compared to that produced by the Dijkstra's algorithm in static conditions which is satisfactory. This indicates that the average performance of the simultaneous optimal search carried out by the mutation operators as part of the PSO-GM contributes significantly towards performance improvements.

Figure 9. Mean Squared Error (MSE) versus Epoch for the 5 operators –Gaussian, Cauchy, Levy, Single-Point and Chaos operators.

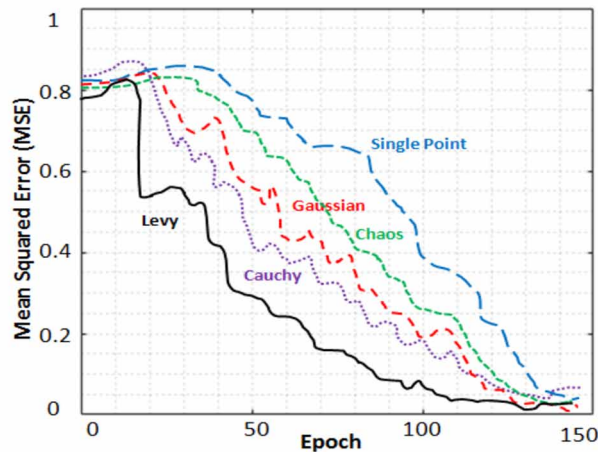


Table 5. Comparison of objective function values obtained against generations from proposed approach and those generated using GA and PSO in SPR in UDN.

Work	Parameter	Remark
(Lindfield et al., 2017)	<i>Convergence Property of Shortest Path Search</i>	The GA based method in Figure 4 and at 6 th generation achieved objective function value of 0.8
(Lindfield et al., 2017)		The PSO based method in Figure 4 and at 6 th generation achieved objective function value of 0.9
Present work		Proposed hybrid PSO-GM method in Figure 4 and at 6 th generation achieved objective function value of 0.7; Proposed approach has better convergence rate.

Finally, we have calculated the MSE associated with each of the five mutation operators in the hybrid PSO-GM model with Dijkstra's Algorithm used as the benchmark. This is shown in Figure 9. The Levy operator has the best convergence while the Chaos operator provides fluctuating performance. These curves are generated from the average of performances derived under all the four traffic conditions with over hundred trials carried out for each of the time window and operator separately.

From the above discussion it is obvious that the proposed hybrid PSO-GM algorithm provides optimal SPR searches in UDNs with loads and conditions varying as the traffic requirements. Further we show in Table 5, a comparison of the Objective Function Values with Generations obtained from the proposed hybrid PSO-GM method and those generated using GA and PSO (Lindfield et al., 2017). The advantage of the proposed approach is obvious.

CONCLUSION

In this paper, we have reported the details of implementation of a hybrid PSO-GM approach in which five different mutation operators are combined to derive the optimal search for determining the shortest route in a dynamic UDN. From the experimental results it is seen that the Levy operator provides the best performance while the Chaos operator shows randomness in the convergence curves. In the actual scenario, for a given search all the operators take part in the operation and the best performing operator at the given point of time gets the predominance to provide the solution. Experimental results have included average performance results to indicate the sustaining capability limits of the approach. This approach is likely to help in providing solutions to congestions to high data rate networks.

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