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A Multi-Objective Particle Swarm Optimisation Approach in Interference Mitigation Underlay 5G-Enabled Machine-to-Machine (M2M) Network in Comparsion with Genetic Algorithm (GA) and Simulated Annealing (SA) Algorithms

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Abstract*— The increase in the number of connected devices has caused a paradigm shift in cellular standards, which has characterized the Long-Term Evolution (LTE) standard. The fifth-generation (5G) standard supports several promising mobile technologies, including Machine-to-Machine (M2M) communication and Device-to-Device (D2D) communication, connecting numerous ubiquitous intelligent devices. M2M communication has found applications across various areas of human activity, such as industrial automation, geological and environmental monitoring, e-health, smart grids, intelligent monitoring, and intelligent transport systems. The deployment of M2M devices underlaid 5G cellular network has introduced new challenges in resource allocation and interference management. Interference due to decreased inter-cell distance and the seamless integration of heterogeneous devices into the 5G cellular network results in degraded Quality of Service (QoS) and network performance. This paper proposes an interference-aware architecture for M2M communication on 5G network to mitigate interference arising from the localization of M2M devices. Furthermore, the proposed interference mitigation scheme will be mathematically modeled as a multi-objective particle swarm optimization (MOPSO) problem, considering the complexity of the fitness function and the trade-off among particles. However, the proposed interference mitigation scheme was bench-marked with Genetic Algorithm (GA) and Simulated Annealing (SA) optimisation algorithms. Simulation results proved that the optimal configuration identification process of the MOPSO has achieved significant improvement in interference reduction from M2M devices relative to GA and SA strategies. Furthermore, the SINR (25.0 dB) and throughput (95.0 Mbps) of the overall network was enhanced with MOPSO in comparison with lower results obtained when GA (SINR 21.5 dB, Throughput 85.0 Mbps) and SA (SINR 18.0 dB, Throughput 78.0) were applied. The improvements achieved by MOPSO shows that the SINR when compared with SA and GA decreased by 28% and 14% respectively. While the throughput achieved by MOPSO when compared with SA and GA showed a decrease by 18% and 10% respectively. Therefore, a balance between optimal M2M separation distance and improved network performance was achieved.

***Keywords*—5G Network, Interference mitigation, Machine-to-Machine (M2M) communication, SINR, Throughput**

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I. Introduction

The rapid increase in data-driven services has led to a significant rise in traffic on cellular networks. It is expected that hundreds of billions of devices will connect through the Internet of Things (IoT) to perform various functions [1]. The increasing densification and diversity of complex communication networks puts significant pressure on available radio resources, which are already limited due to the scarcity of spectrum. This situation presents various challenges. Next-generation communication technology aims to connect people, devices, applications, and transportation systems. The system links cities by creating smart networked communication environments to move data quickly with minimal processing time [2]. Cellular communication underpins all communication linkages and will be instrumental for implementing Internet of Things (IoT) devices and Machine-to-Machine (M2M) devices as well as Device-to-Device (D2D) communication in successful systems [3-5]. The fifth-generation (5G) mobile network standard includes standard infrastructure availability together with ease of installation and maintenance while providing extensive Machine-Type Communication (MTC) and improved speed. The advanced features of 5G networking systems differ remarkably from what previous mobile standards such as Long-Term Evolution (LTE) and the third Generation Partnership Project provided [6].

The geographic relationships between connected devices through M2M (Machine-to-Machine) communication enhances both area reuse factors and communication efficiency. Through autonomous connection devices can link to the network utilizing different access points independently of human operators. Multiple devices connect directly through M2M communication to establish a system that accepts Internet of Things (IoT) devices along with actuators and smart sensors to bring many devices together across various application areas. The 5G cellular standard will extensively support M2M communications implementation during its deployment. Compared to earlier generations of mobile networks, 5G aims to provide ultra-reliable, low-latency communication (uRLLC), along with support for massive machine-type communication (mMTC) and enhanced mobile broadband (eMBB).

Applications that can benefit from M2M technology include smart agriculture, wearable sensors, surveillance systems, smart grids, smart meters, health monitoring equipment, intelligent transit terminals, and industrial automation machines [7]. In M2M communications, data transactions at each device typically involve only small amounts of data, making LTE and LTE-A technologies inefficient for these purposes, as they were primarily designed for wideband applications [8]. All of these low-power, low-complexity devices can connect wirelessly through machine-to-machine (M2M) communication [9]. Ensuring reliable wireless connectivity for network services with strict requirements for availability, latency, and reliability is the primary objective of uM2M [10].

The integration of diverse devices and the rising density of machine-to-machine (M2M) devices in cellular networks—resulting from decreased inter-cell distances—pose significant challenges, especially in managing interference[11]. These factors complicate interference management and resource allocation for M2M communications. As a result, they can reduce channel capacity, negatively affecting the communication quality for primary users [12]. In 5G networks, two common types of interference are co-channel interference (CCI) and adjacent channel interference (ACI)[13], [14]. These challenges stem from the architecture of densely populated, heterogeneous 5G networks, where reduced inter-cell distances result in devices being in constant communication. This situation leads to significant interference issues that can degrade communication quality. Co-channel interference occurs when multiple devices share the same frequency resources. In contrast, adjacent channel interference happens when devices share different frequency resources but still reuse portions of the cellular spectrum. Additionally, mutual interference arises from the proximity of similar transceivers within each other's communication range.

The key contributions of this work are stated as follows:

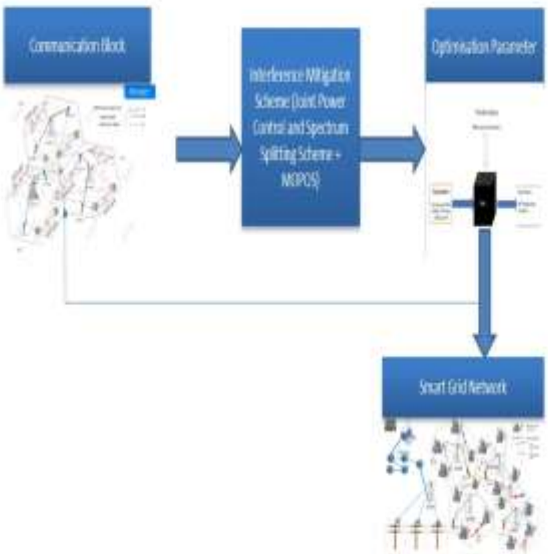
i. Proposes the design and development of an interference-aware architecture that includes an interference mitigation scheme specifically for 5G networks, with applications to the Nigerian power grid.
ii. Mathematically models the interference mitigation scheme as a Multi-Objective Particle Swarm Optimization (MOPSO) problem, incorporating distance, power, and bandwidth as the multi-objective parameters.

The remainder of this paper is organized as follows: Section II covers the related works associated with the fundamental concepts of interference. Section III presents the proposed interference-aware architecture and the Multi-objective Particle Swarm Optimization (MoPSO) scheme designed for interference mitigation. Section IV outlines the anticipated results, and Section V contains the concluding remarks.

II. RELATED WORKS

In the literature, interference in Machine-to-Machine (MM) communications within 5G networks has generally been addressed through a variety of strategies. These strategies include radio resource allocation, power control techniques, and spectrum allocation to mitigate interference issues. The challenges of interference in ultra-dense tiny cells, especially those using Network Flying Platforms, are also explored by [15]. The study examines NP-hard problems and suggests suboptimal solutions for minimizing interference using a bipartite machine and a local search-based algorithm. However, a significant limitation of the research is its failure to consider cross-tier interference. Despite not accounting for cross-tier interference and user mobility, the simulation results demonstrated effective interference minimization. HAPPIER is a learning-based interference management system specifically designed for tiny cells mounted on unmanned aerial vehicles as proposed by [16]. Reinforcement learning and hybrid affinity propagation clustering work together to control Autonomous Small Cell power transmission for co-channel interference reduction purposes. The gearbox power adjustment enables the system to reach 93% of the total throughput levels beyond exhaustive search methods. The research mainly concentrated on M2M cross-interference without investigating co-channel or mutual interference. The research by [17] proposed an efficient strategy to boost system throughput for Machine-to-Machine (M2M) devices functioning on cellular networks while building an extensive methodology. The proposed method employs cell subdivision as part of its distribution scheme along with channel allocation and a reliable power allocation process through particle swarm optimization for mid-cells. Improved interference reduction from simulations produces improvements in system throughput [18]. The network throughput significantly decreases when M2M pairings reach a specific threshold beyond which they cannot maintain proper communication. Implementation of the study focuses on co-channel and cross-channel interference problems without investigating mutual interference.

According to the research conducted by [19] there is a



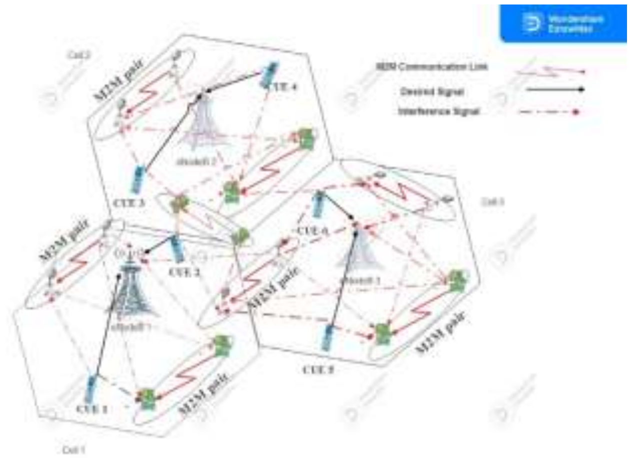


Fig 1: System Model for M2M communications in uplink multi-cell network

Fig 2: Block diagram of the proposed interference-aware scheme

negative influence on signal-to-interference plus noise ratio (SINR) when eNodeB power decreases despite increasing throughput requirements. Although SINR improves significantly with higher throughput demands and during outages, the study overlooks cross-tier interference from neighbouring multi-cell environments. Additionally, it does not address co-tier and mutual interference. An analysis of various techniques used by researchers indicates that current interference mitigation strategies are incomplete. Specifically, they frequently neglect cross-tier interference, co-tier interference, and mutual interference. This gap in existing research highlights the necessity for the approach taken in this study.

III. SYSTEM MODEL AND DESCRPITION

This paper presents a system architecture designed to address inter-cell interference in a heterogeneous network (HetNet), which consists of one eNodeB and two Cellular User Equipment (CUE) and a pair of M2M device. The study specifically focuses on the worst-case scenarios of interference in an eNodeB to CUEs, CUE-to-M2M pair, and between M2M pair considering both co-tier and cross-tier interference, co-channel and mutual interference. The model aims to minimize interference and while maximizing throughput and SINR, particularly in the context of machine-to-machine communication in a multi-cell environment. The system model utilizes a centralized resource allocation architecture that is managed by the eNodeB as depicted in Figure 1, while Figure 2 depicts a diagrammatic representation of the overall model showing the parameters, network constraints and the system performance metrics. The components of Figure 2 comprised the communication block which encompasses the CUEs, Machine-Type-Devices (MTD) and eNodeB; followed by the MOPSO algorithm and the optimisation parameters which represents the elucidated radio condition requirements.

3.1 Problem Formulation

Within the serving eNodeB of an Orthogonal Frequency Division Multiple Access (OFDMA) network, there are Z sub-channels with K-MTDs and L-CUEs coexisting. With as many available channels as there are CUEs in each eNodeB, the network runs at maximum capacity. Cellular subscribers' uplink channels (UL) are shared by M2M connectivity. Each M2M pair employs one Resource Block (RB), and there are index sets of cells, CUEs/channels, and MTDs represented by Furthermore, it is also assumed that M2M links share $z-th$ uplink channel (UL) $Z_C=\{1,2,3,.......Z\}$, which are used by the cellular user. Let the index sets of the cells, CUEs/channels, and MTDs be represented by $eN_s=\{1,2,3.........eN_{sm}\}$, $P=\{1, 2,3,..., Z\}$ and $Q=\{1, 2,3,.., K\}$ respectively. It is equally assumed that $\kappa=[1,2......K]$ is a set of Resource Block where each M2M pair uses one RB and that each RB can be shared by one M2M pair. Only by sharing RBs with CUEs can M2M pairings establish a connection. The eNodeB computes the channel state information (CSI) of cellular uplinks, and the network's frequency reuse is taken to be one. Furthermore, a fully loaded network in which M2M pairs can only connect by sharing RBs with CUEs was also considered. When an MTD pair is communicating directly with the serving eNodeB, the receiver (M2M-Rx) and transmitter (M2M-Tx) do not need to be in the same cell. In Figure 1, an M2M (M2M-Tx) is allowed to communicate directly with an M2M (M2M-Rx) if the designated M2M (M2M-Rx) is within the transmission range of the M2M (M2M-Tx). MTDs can be assigned with RBs and power control strategies, and where M2M devices provide routes for communication convenience.

Taking into consideration different QoS requirements, our goal is to identify an effective joint channel allocation, power control strategy and the optimal communication distance for each M2M transmitter in the multicellular scenario. We assume that the channel transmission rates required for each service vary and that M2M users have K service kinds, denoted by $F_k \in \{F_1, F_2, F_3 \ldots\ldots F_K\}$ and that each service requires a different channel transmission rate. By leveraging numerous channel resources to ensure packet transmission success, we postulate that an M2M pair can meet the QoS requirements of the entire communication system with minimal power consumption. Furthermore, the CUE's signal to interference-plus-noise-ratio (SINR) can be written as $\xi_j^{C_n}$. The SINR must be higher than ξ^* for transmission to be successful. Where ξ^* the threshold for different M2M devices. Therefore,

$$\xi_j^{C_n} > \xi^*, \ \forall j \in N \tag{1}$$

For the nth M2M link on the j th channel, the SINR is expressed as:

$$\xi_j^{M_n} = \frac{P_j^{M_n} e_j^{M_n}}{P_j^{C_m} e_j^{C_m} + \sum_{h=1, h\neq n}^{N} P_j^{M_h} e_j^{M_h} + N_a + \sigma^2} \tag{2}$$

Where $P_j^{M_n}$ is the transmit power on the M2M link on the j th channel and $e_j^{M_n}$ denotes the channel gain between the M2M-Tx and M2M-Rx respectively. Moreso, $P_j^{C_m}$ on the j th channel represents the transmit power by the m th CUE and $P_j^{M_h}$ denotes the transmit power of the h th M2M link. The link gain of the m th CUE and h th M2M link on the j th channel are denote by $e_j^{C_m}$ and $e_j^{M_h}$ respectively. The Additive White Gaussian Noise (AWGN) power is given as σ^2 , N_a represents the average interference (Noise) emanating from other surrounding neighbouring cell which can be expressed as:

Similarly, the SINR of the m th CUE on the j th channel can be denoted as:

$$\xi_j^{C_n} = \frac{P_j^{C_m} e_j^{C_m}}{\sum_{i=1}^{K} \sum_{y=1,}^{N} P_i^{M_y} e_i^{M_y} + N_a + \sigma^2} \tag{3}$$

Where the transmit power of the m th CUE and the transmit power of the y th M2M link the reusing the i th channel is given as $P_j^{C_m}$ and $P_i^{M_y}$ respectively, while the channel gain of the m th CUE and the channel gain of the y th M2M link reusing the i th channel is denoted as $e_j^{C_m}$ and $e_i^{M_y}$ respectively as shown in equation 3.

$$N = E \cdot \sum P_W \cdot S_W^{-\alpha} \qquad \forall w \in \{1,2,3,\ldots.W\} \tag{4}$$

The overall system capacity of a given cell is expressed as:

$$\max_{\omega_{i,j}, P^m{}_j} R_{overall} = \sum_{b\in N_S} \sum_{i\in P} \left[B\left(\log_2(1+\xi_j^{C_n}) + \sum_{j\in Q} \omega_{i,j} \log_2(1+\xi_j^{M_n})\right) \right] \tag{5}$$

Where B represents the bandwidth.

3.2 Multi-Objective Particles Swarm Optimisation (MOPSO) for Power, Spectrum and Distance Allocation

The social behaviour of particles, like the movement of fish or birds, served as the inspiration for the well-known population-based metaheuristic technique known as particle swarm optimisation. MOPSO serves as a superior optimization tool than GA, SA, ACO, and ABC because it combines efficient computation with fast convergence along with its capability to optimize multiple objectives simultaneously [20-21]. MOPSO applies swarm intelligence methods while employing leader archive mechanisms for memory management and adds cognitive and social rules to its velocity update process. MOPSO proves most suitable for SINR and throughput balancing applications and its adaptive versions enhance the balance between exploration and exploitation. The system sustains its operation in shifting conditions to deliver real-time adjustments during runtime. The parallel design of this algorithm enables detachment of particle assessment from each other which prevents slowdowns because of changing network conditions and device mobility.

The position and velocity of each particle are the main parameters in this algorithm. Each particle adjusts its location inside the multidimensional search space based on its own experiences as well as those of its neighbours. Local and global search techniques are combined in the PSO approach [22]. The PSO method is initialised by selecting the particle's initial position at random, and the fitness value is then calculated using the objective function[23]. Each particle gets closer to Pbest and Gbest, the two ideal values, with each repetition. Pbest is the best solution each particle has generated, and Gbest is the best response from the population [24]. In this research, the M2M transmitter learns an efficient joint channel splitting and selection with power control policy after interacting with the environment. In general, M2M users' transmission power rises and cellular users see higher interference when more M2M users use the cellular channels. By enabling each M2M pair to adaptively optimise and trade-off multi-object particles (channel bandwidth, the best M2M separation distance, and power control approaches), our methodology maximises SINR and system ergodic capacity while meeting service expectations. The aforementioned problem is a complicated multi-objective dilemma that can be addressed with the aid of Multi-objective Particle Swarm Optimisation (MOPSO) approaches[25].

3.2.1 Particle Initialisation

$$X = [Power, Bandwidth, Distance] \tag{6}$$

Each of the particles are expressed as vector and with several particle population can be given as follows:

$$X_{i,j} = [P_{i,j}, B_{i,j} \ \ D_{i,j}] \tag{7}$$

$$X_{i,j} = \begin{bmatrix} P_{i,j}{}^{n} \\ B_{i,j}{}^{n} \\ D_{i,j}{}^{n} \end{bmatrix} \quad (8)$$

Where $\mathbf{P}i,j(n)$ is the Power parameter P for the n-th sample at position (i,j), $\mathbf{B}i,j(n)$ is the Bandwidth parameter B for the n-th sample at position (i,j), $\mathbf{D}i,j(n)$ is the Distance parameter D for the n-th sample at position (i,j).

3.2.2 Fitness Evaluation: The objective function of the MoPSO is to maximise both the overall system throughput and SINR which can br expressed as:

$$maximize\ \left(G\left(X_{i,j}\right)\right) = \ [SINR,\ Th_{overall}] \quad (9)$$

Subject to: $P_{\min} \le P_i \le P_{\max}$, $B_{\min} \le B_i \le B_{\max}$, $D_{\min} \le D_{i,j} \le D_{\max}$ where the minimum and maximum Power, Bandwidth and Distance constraints respectively.

3.2.3 Velocity and Position Update: The velocity and position for each particle are regularly updated which is based on its current position, personal best and global best using the below equation.

$$v_i^{(t+1)} = wv_i^{(t)} + c_1 r_1 (p_i^{(t)} - x_i^{(t)}) + c_2 r_2 (g^{(t)} - x_i^{(t)}) \quad (10)$$

where are the particle's i velocity $v_i^{(t)}$ at time t, given the inertia weight w (which regulates the trade-off between exploration and exploitation), c_1 and c_2 represents the acceleration coefficients for cognition and society, respectively. The MOPSO could achieve the necessary trade-off between social and cognitive behavioural patterns by modifying c_1 and c_2 , which are random numbers evenly distributed between 0 and 1. These are the particle's personal best $p_i^{(t)}$ i position and the global best position $g^{(t)}$ that all of the particles i in the swarm have explored. The location of the particle is updated as [26]:

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \quad (11)$$

*3.2.4 Pareto Front Update and Non-Dominated Sorting***:** For multi-objective optimisation, the algorithm uses a non-dominated sorting technique to update the Pareto front, evaluate the values of the objective function, and update particle locations and velocity. A solution x_i dominates another solution x_j based on the below stated condition:

If and only if:

1. $SINR_i \geq SINR_j$ and $Throughput_i \geq Throughput_j$
2. Atleast one inequality is strict.

*3.2.5 Archive Update***:** Several non-dominated solutions that satisfy the Pareto optimality requirement are stored in the archive. When the finest new solutions are found, the archive is updated on a regular basis.

3.2.6 Convergence Check: Depending on the needs of the network, the algorithm converges to a set of Pareto-optimal solutions that balance SINR and throughput. The network's preferred network will ultimately determine the choice.
The flow chart of the Multi-Objective Particles Swarm Optimisation algorithm is shown in Fig. 3.

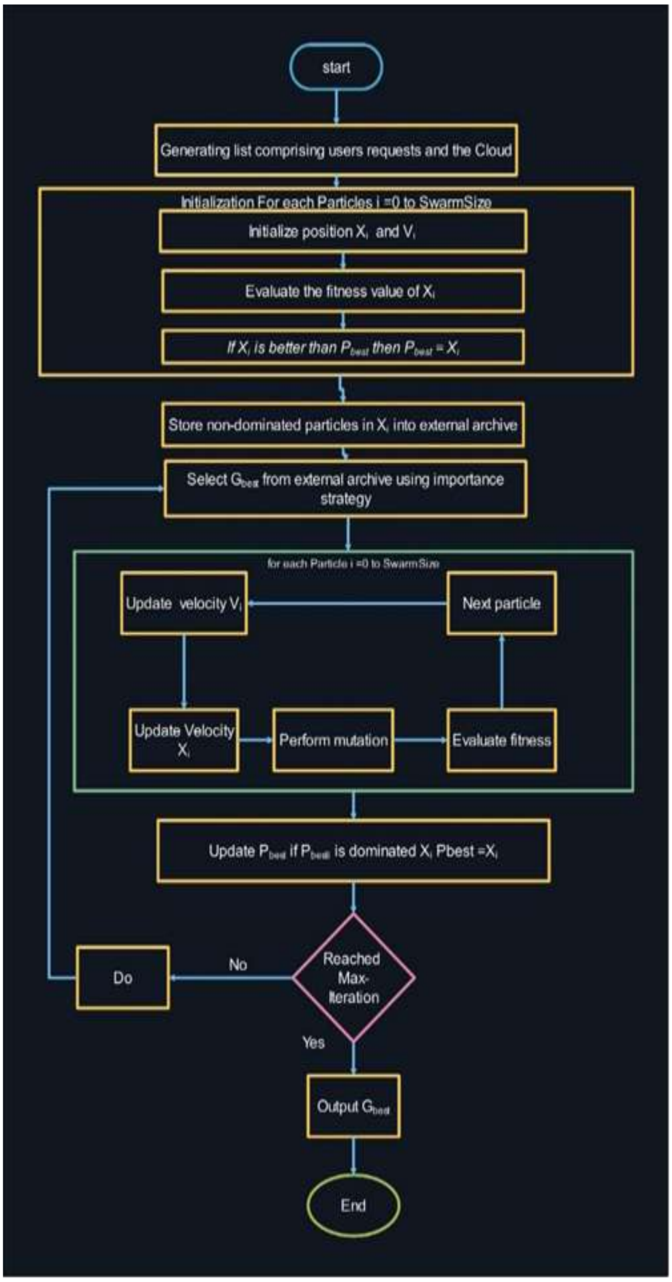


Fig 3: The flow chart of the Multi-Objective Particle Swarm Optimisation (MoPSO)

IV. Simulations and Results

In this section, we use in-depth MATLAB simulations to assess the performance of MOPSO algorithm using MATLAB R2024a with the simulation parameters shown in Table I. The simulation was conducted for 500 iterations and was bench-marked with other similar algorithm such as Genetic algorithm and Simulated Annealing (SA) whose simulation parameter are also depicted by Table II and Table III respectively.

TABLE I. SIMULATION PARAMETERS FOR MOPSO

Simulation Parameters	
Parameters	**Values**
MTD Transmission Power	**17.2dBm**
MTD Distance of Separation	**20m**
CUE Transmission Power	**100mW**
Swarm Size	**50 – 100**
Number of Iterations	**500**
Inertia Weight	**Linearly decreasing from 0.9 -0.4**
Cognitive and Social Coefficient ($c_1 \& c_2$)	**1.5 - 2.0**
Velocity Limits	**10% to 20% of the search space**
Position Limits	**Power, Bandwidth and Distance constraints**
Mutation Rate (for Diversity)	**0.1 to 0.3 (applied to global)**
Archive Size (for Storing non-dominated solutions)	**50**
Leader Selection	**Crowding Distance**
Fitness Function	**Maxmising SINR & Throughput**
Constraint Handling	**Penalty Function**

TABLE II. SIMULATION PARAMETERS FOR GENETIC ALGORITHM

Parameters Setting	Genetic Algorithm (GA)
Population Size	**50 -100**
Selection Method	**Tournament Selection (Size 3)**
Crossover Rate	**0.8 – 0.9 (Single-Point Crossover)**
Mutation Rate	**0.01 -0.05**
Elitism Rate	**5%**
Number of Generations	**500**
Stopping Criteria	**Max. Number of generation (500) No significant improvement over 50 generations**
Fitness Function	**Maximising SINR & Throughput**
Constraint Handling	**Penality Function for Constraint voilations (Distance between M2M pairs, Bandwidth, Power)**

TABLE III. SIMULATION PARAMETERS FOR SIMULATED ANNEALING

Parameters Setting	Simulated Annealing (SA)
Initial Temperature	**1000**
Cooling Schedule	**Exponential (($T_{new} = \alpha \bullet T$)) where** α=0.95
Minimum Temperature	**0.01**
Number of Iteration per Temperature	**50**
Acceptance Probability	**Boltzmann Distribution**
Number of Generations	**500**
Neighbourhood Structure	**Small pertubations in decision variables (power adjustments)**
Objective Function	**Maximising SINR & Throughput**
Stopping Criteria	**Minimum Temperature reached Maximum iterations (500) No improvement after a fixed number of iterations (100)**

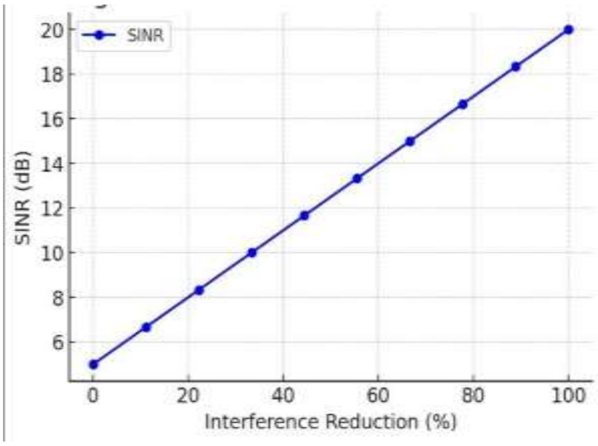


Fig 4:Graph demonstrating how reduction in interference enhances the Signal-to-Interference-plus-Noise Ratio (SINR).

The distance between machine-to-machine pairs significantly affects the SINR and throughput along with interference while operating in heterogeneous 5G networks as shown in Fig.4. Signal propagation together with path loss and power control systems influence this phenomenon. Reducting the M2M pairs distance increases received signal power. Higher signal-to-interference-plus-noise-ratios (SINR) along with better throughput and lower interference occurs when power transmission remains minimal. The impact of pathloss becomes more severe when the transmission distance is increased leading to a decrease in SINR thereby limiting the achievable throughput. Higher network interference results from implementing increased transmit power levels. During this scenario, the network operating at longer distances becomes more affected by co-channel and inter-cell interference from neighbouring transmitting signals. The application of adaptive resource distribution systems, interference management skills, and efficient control procedures are necessary to maintain trade-off and performance levels at varying distances as shown in the simulation.

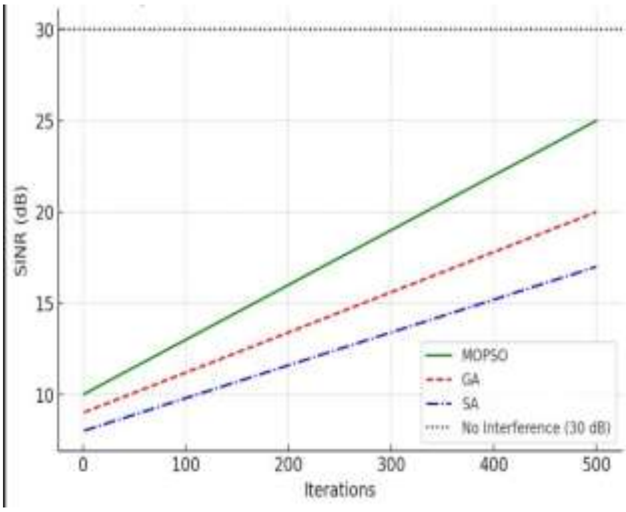


Fig 5a: SNIR without interference

The Signal-to-Interference-plus-Noise Ratio (SINR) has improved the most by MOPSO, followed by Genetic Algorithm (GA) and Simulated Annealing (SA) as depicted in Fig 5a in the absence of interference. The dashed black line, which shows the SINR at 30 dB without interference, emphasises how much interference can lower the impact of SINR. This impact results in the decrease of transmitted signal quality. Additionally, MOPSO performs better than the other approaches in terms of throughput as show in Fig 5b, relative to other optimisation approaches such as GA coming in second and SA last. Interference significantly reduces network throughput, as seen by the dashed black line, which represents the throughput without interference, set at 100 Mbps.

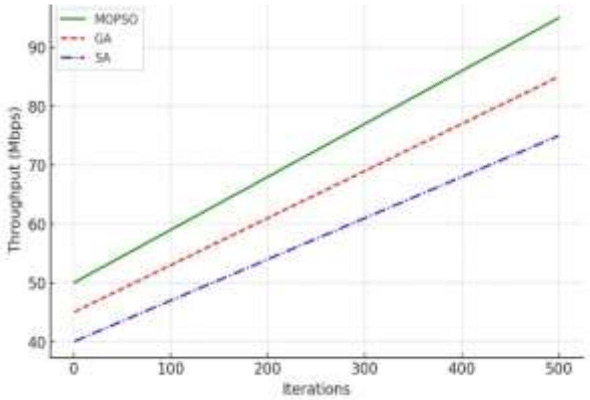


Fig 5b: shows throughput without interference

The Signal-to-Interference-plus-Noise-Ratio (SINR) experienced increasing improvement through 500 iterations when using optimisation algorithms SA, GA and MOPSO as depicted in Fig 6. The algorithm of MOPSO shows the highest SINR enhancement during 500 runs because it develops SINR from 10dB to 25dB. MOPSO demonstrates both optimal interference reduction and consistent SINR enhancement because of its effective optimal configuration identification process. The Genetic Algorithm shows an average level of enhancement as its performance starts from 9 dB before ending at 20 dB after executing 500 iterations. The SINR of Simulated Annealing grows most gradually out of all three algorithms since it starts at 8 dB and reaches just 17 dB. The moderate increase in outcomes demonstrates that SA faces difficulties overcoming local search traps thus resulting in subpar reductions of interference. The progressive optimization rate of GA becomes reduced for optimizing SINR when compared to other conditions. MOPSO demonstrates superior performance over both GA and SA because it employs swarm-based techniques that lead to effective optimization of power distribution and bandwidth utilization as well as interference reduction. MOPSO outperforms GA in terms of maximizing SINR performance though GA achieves better results than SA due to premature convergence issues. SA achieves the least successful outcome in this scenario because its probabilistic exploration cannot consistently identify superior SINR configurations.

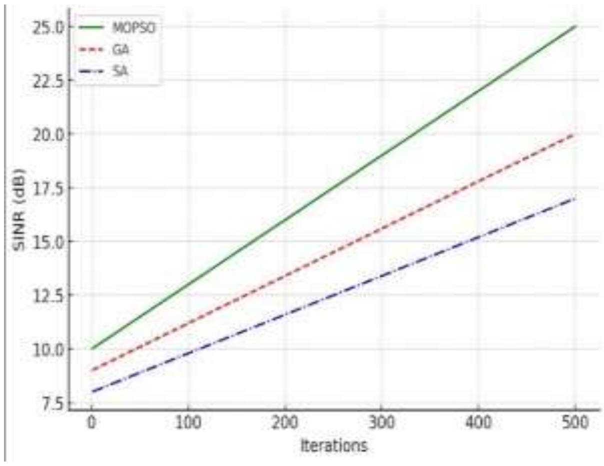


Fig 6: Comparison of Signal-to-Interference-plus-Noise Ratio (SINR) of MOPSO, GA and SA

The throughput result using MOPSO reaches 95 Mbps during 500 iterations as shown in Fig 7. MOPSO demonstrates efficient identification of optimal resource allocation methods which maximize throughput through power control together with bandwidth allocation and M2M pair distance settings. The steady and stable growth pattern demonstrates that MOPSO achieves optimal exploration-exploitation balance to achieve stable convergence. The performance metrics of GA exhibit an acceptable strength that progresses from its initial 45 Mbps throughput to reach 85 Mbps at iteration 500.

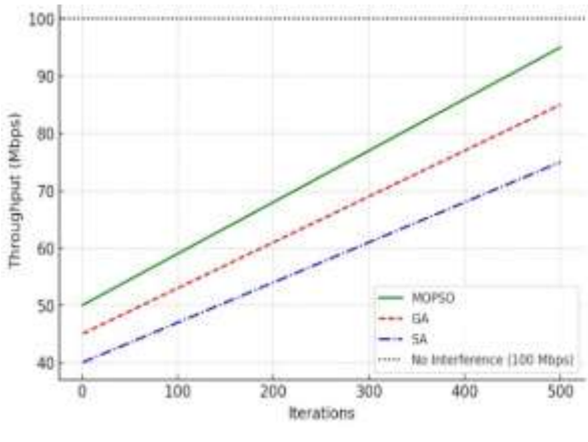


Fig 7**:** Comparison of Throughput (Mbps) of MOPSO, GA and SA

The throughput improvement achieved by GA falls short of what MOPSO could achieve. The genetic operations employed in MOPSO demonstrate better performance for locating the global optimum as opposed to the selection, crossover and mutation methods in the study. MOPSO reaches global optimum at a much faster rate than GA according to its performance curve. When it comes to throughput gain SA demonstrates the slowest pace of improvement. The algorithm managed to reach 75 Mbps as its maximum throughput during 500 cycles while starting at 40 Mbps. The minimal speed of throughput improvement indicates that SA struggles to discover optimal solutions because it experiences issues with finding local optimum solutions. Probability-based designs of SA create less trusted enhancements by using random modifications to discover superior solutions. MOPSO's swarm intelligence method successfully completes space searches and tunes power control parameters and modulation methods as well as interference management tools to produce its advanced performance levels. Genetic Algorithms (GA) achieve only minimal better performance levels because their genetic operations often encounter premature convergence in addition to requiring significant time to produce optimal solutions. Furthermore, the use of random operators makes genetic algorithms less efficient when allocating resources and control of M2M transmission power, hence resulting in low throughput and SINR after several iterations.

SA proves to be the least successful approach among the methods because its extensive exploration phase combined with local optimum trapping results in reduced throughput outcomes. The swarm-based optimization through MOPSO significantly improves power distribution and bandwidth utilization and interference management which produces superior performance than both GA and SA. The GA optimization performance exceeds SA but encounters premature convergence problems thus yielding inferior results than MOPSO in maximizing SINR. The probabilistic exploration method deployed in SA proves to be the least effective strategy since it does not achieve consistent optimal SINR configuration and it inappropriate for minimizing network interference when dealing with ultra-dense heterogeneous networks containing numerous base stations as well as mobile users and M2M communications. Table IV shows a comparative analysis of various performance metrics for the proposed MOPSO algorithm when benchmarked relative to both GA and SA.

TABLE IV. QUNATITY PERFORMANCE COMPARING SIMULATED ALGORITHM (SA), GENETIC ALGORITHM (GA) AND MULTI-OBJECTIVE PARTICLES SWARM OPTIMIMSATION (MOPSO) ALGORITHMS

Metrics	SA	GA	MOPSO
Best SINR (dB)	18.0	21.5	25.0
Average SINR (dB)	17.2	19.8	22.5
Worst SINR (dB)	15.5	18.0	20.0
Best Throughput (Mbps)	78.0	85.0	95.0
Average Throughput (Mbps)	75.8	81.2	90.5
Worst Throughput (Mbps)	72.0	76.0	85.0
Execution Time (Seconds)	50	45	30
Convergence Speed (Iterations)	400	350	250
Stability (Variance)	High	Medium	Low
Solution Diversity	Low	Medium	High
Exploration Ability	Low	Medium	High
Exploitation Ability	Medium	High	Medium

V. CONCLUSION

In this study the problem of interference mitigation was studied which encompasses co-channel, adjacent channel and mutual interference. However, the Multi-Objective Particles Swarm optimisation (MOPSO) scheme was implemented to ascertain the optimal resource allocation via trade-off between SINR and overall network throughput based on the constraints of power, bandwidth and mutual distance between M2M pairs. The speedy convergence attribute of the MOPSO represents the best approach to optimize throughput combined with Signal-to-Interference-plus-Noise-Ratio (SINR) performance in 5G systems thus suited for resource allocation and interference control objectives. Hence the significant improvement in both SINR and throughput achieved via simulation results. In comparison with alternative solution Genetic Algorithms (GAs) needs manual parameter adjustments to improve their convergence speed. The random search method in Simulated Annealing makes this algorithm unsuitable for the case because it cannot optimize throughput and reduce interference effectively in this particular context.

The potential of MOPSO to optimize 5G operations exists while it encounters issues with performance calculation together with convergence and real-time adjustment requirements. The effective use of hybrid methods and adaptive techniques and edge computing makes MOPSO suitable for implementing in next-generation networks which require stringent performance.

High complexity of computation with an enormous swarm size and numerous iterations demands a substantial amount of processing power from MOPSO. However, 5G networks' changing channel conditions and high data throughput requirement makes real-time optimisation difficult considering the dynamic time invariant nature of the communication channel and load dynamics. To decrease the execution time, the utilisation of distributed computing or parallel processing is highly recommended. In addition, the sensitivity and selection process of parameters (e.g., inertia weight, cognitive and social coefficients) has a significant impact on MOPSO performance to avoid the situation leading to early convergence due to unsuitable parameter adjustment. Adjusting parameters dynamically by utilising self-tuning or adaptive processes can mitigation the challenge of unsuitable parameter adjustment. Managing trade-offs with multiple objectives might be challenging in attaining the optimal balance between several objective functions since they frequently clash. It can be subjective to choose the optimal compromise option from a Pareto front in determining the best trade-off, through utilising multi-criteria decision-making (MCDM) methodologies. Adaptation in real-time entails that MOPSO must make real time adjustment to changes in dynamic 5G and beyond settings, including as interference levels and user mobility through the process of creating adaptable versions that react to changes in the environment without the necessity of re-execution. Issues with scalability gets harder to sustain peak performance as the network grows as the optimisation procedure may be overloaded by a large number of users and devices.

Finally MOPSO in the future has shown the propensity to be deployed in various verticals ranging from edge computing servers requiring real-time optimisation with stringent requirment for low-latency, also in the aspect of energy efficiency through minimsation of power consumption in 5G eNodeB and low-power devices.

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