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Metaheuristic multi-objective access selection in hetNets over a secure MPLS networks

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ABSTRACT

Maintaining acceptable video quality during mobility remains a key challenge in heterogeneous networks (HetNets), especially when user equipment (UE) performs frequent vertical handovers between different access technologies. This work proposes an AI-driven handover management framework designed to preserve video Quality of Experience (QoE) during network-layer mobility, while operating over a secure MPLS core backbone. In the proposed system, all mobile hosts are Mobile IPv6 (MIPv6) enabled and handovers are executed through standard MIPv6 procedures as the UE moves across LTE/Wi-Fi access networks. The framework combines two complementary components. First, a lightweight multilayer perceptron (MLP) model predicts video QoE indicators, namely Mean Opinion Score (MOS) and Peak Signal-to-Noise Ratio (PSNR), from real-time QoS measurements (throughput, end-to-end delay, jitter, packet loss) while also considering UE energy consumption. Second, based on these QoE predictions, we introduce a new fitness score that jointly combines predicted QoE and normalized QoS indicators into a single decision metric. This fitness score is exploited by an SDN controller based access selection mechanism, where metaheuristic optimization algorithms, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), are used to rank candidate access points and select the most suitable LTE/Wi-Fi attachment option. The proposed approach is evaluated through OMNeT++/INET simulations in a secure MPLS based HetNet scenario supporting continuous video streaming and is compared against a conventional RSSI based handover strategy. The results show that combining QoE prediction with the proposed fitness based, metaheuristic driven access selection improves handover stability and video continuity, while significantly reducing packet loss, jitter, and end-to-end delay, increasing throughput, and enabling more energy-aware and QoE oriented mobility management.

1 Introduction

The continuous growth of mobile multimedia services especially real-time video streaming, has significantly increased the demand for uninterrupted connectivity and stable Quality of Experience (QoE) in mobile environments[1]. Modern access infrastructures are heterogeneous, combining multiple radio access technologies such as LTE/5G and Wi-Fi[2]. These heterogeneous networks (HetNets) offer improved coverage and capacity, but they also introduce frequent vertical handovers (HOs)[3] when the user equipment (UE) moves between different access points and technologies. During such transitions, video sessions become sensitive to packet loss, delay spikes, jitter, and throughput degradation, which can significantly reduce quality and cause interruptions. Ensuring handover continuity is therefore not only a radio access problem but also an end-to-end challenge that involves the access segment, the mobility management layer, and the transport/core backbone. While many handover strategies focus mainly on radio metrics such as RSSI or SINR, video performance depends on a broader set of QoS indicators that influence application level QoE. In addition, energy consumption is a critical constraint because frequent scanning and handover execution can drain the UE battery, especially when the decision logic triggers unnecessary "ping-pong" transitions between access networks. In this context, network layer mobility protocols, such as Mobile IPv6 (MIPv6), remain attractive because they provide standardized IP-layer handover support and maintain session continuity across heterogeneous access networks[4]. However, MIPv6 procedures alone do not guaranties good QoE, since the protocol primarily ensures reachability and does not optimize the choice of the best target access network for video service continuity. As a result, enhancing MIPv6-based mobility with QoE-aware decision mechanisms becomes essential for video streaming scenarios.

Another important aspect in handover optimization is the security and QoS guaranties of the core network[5]. In many practical deployments, heterogeneous access networks are interconnected through an engineered backbone such as Multi-Protocol Label Switching (MPLS)[6,7]. MPLS enables traffic engineering, controlled routing, and QoS enforcement, and can offer improved isolation for sensitive multimedia flows. In this work, the HetNet is interconnected through a secure MPLS core, ensuring that handover related traffic and video flows are carried over a protected backbone that preserves performance and reduces exposure to network threats. To handle the complex and multi-criteria nature of HetNet handovers, artificial intelligence techniques have

gained increasing attention. In particular, machine learning models[8,9] can infer QoE directly from observed QoS measurements, enabling proactive decisions instead of reactive handovers triggered only after service degradation occurs. Nevertheless, QoE prediction alone is not sufficient: selecting the "best" access point in a dynamic HetNet remains a multi-objective optimization problem involving conflicting goals such as maximizing QoE and throughput, minimizing delay and packet loss, and reducing UE energy consumption. Conventional optimization methods often become inefficient under non-linear constraints, discrete search spaces, and rapidly changing mobility conditions. For this reason, metaheuristic optimization algorithms[10,11] have emerged as effective tools for vertical handover and network selection problems[12]. Algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are well suited for multi-objective, non-convex decision spaces because they can explore candidate solutions efficiently and approximate near-optimal choices within reasonable computational time. Their flexibility allows integrating different handover criteria into a unified fitness function, making them practical for QoE-aware mobility management in HetNets. In this paper, we propose an integrated handover optimization framework for video streaming over a secure HetNet infrastructure. The proposed solution combines QoE prediction and metaheuristic access selection under SDN control[13,14], while relying on MIPv6 as the underlying mobility execution mechanism. A lightweight multilayer perceptron (MLP) predicts MOS and PSNR from real-time QoS metrics such as throughput, delay, jitter, and packet loss, and is used to anticipate quality degradation. When predicted QoE becomes unacceptable, an SDN controller activates an optimization module based on GA or PSO[15] to rank candidate Wi-Fi/LTE access points and select the attachment option that maximizes perceived video quality while also accounting for UE energy consumption and signal strength. The main contributions of this work can be summarized as follows:

- QoE-driven handover prediction for video streaming: we design an MLP based model that predicts MOS and PSNR from QoS measurements, enabling proactive detection of video quality degradation. The predicted QoE (MOS,PSNR) is then mapped to an initial fitness score which represents a discrete quality level of the current connection.
- Metaheuristic multi-objective access selection: we integrate GA and PSO inside an SDN controller to rank LTE/Wi-Fi candidate attachments using a composite fitness function combining QoE, QoS, RSSI, and UE energy consumption.

The remainder of this paper is organized as follows: Section 2 reviews related work on QoE/QoS-aware handovers and metaheuristic optimization in heterogeneous networks. Section 3 presents the system model, including the network layout, the MOS/PSNR prediction model, and the GA/PSO-based access selection mechanism. Section 4 reports and discusses the simulation results and performance evaluation. Finally, Section 5 concludes the paper and outlines future research directions.

2 Related works

Optimizing handovers (HO) is a key challenge in heterogeneous networks. These networks, which include different access technologies like cellular and Wi-Fi, require careful coordination to work together smoothly. Recent research has moved beyond single metric designs, increasingly using multi-objective HO optimization. This approach aims to balance conflicting requirements, such as latency, throughput/bandwidth, energy/power consumption, signaling overhead, and handover failure rate[16]. Artificial intelligence methods are usually categorized into three main types: supervised learning, unsupervised learning, and reinforcement learning. Regression techniques, such as those used to predict signal quality or mobility patterns, are commonly employed. Classification methods, for instance, are utilized to determine the appropriateness of initiating a handover. In this study focuses on using metaheuristic optimization algorithms to help with HO decision making[17]. Metaheuristics are well suited for solving HO problems because these problems often have nonlinearities, multiple constraints, and sometimes non-convexities. They also usually involve several conflicting objectives and real-time limitations. Metaheuristics are adept at navigating expansive solution landscapes, and near optimal solutions in a reasonable timeframe. These systems also provide the adaptability to integrate various HO criteria, such as quality of service and experience goals, load distribution, and energy efficiency. Furthermore, they can adjust to evolving network. Genetic algorithms[18], particle swarm optimization[19,20], ant colony optimization[21], simulated annealing, and differential evolution are frequently employed in wireless networking for multi-objective and constrained optimization problems. The performance of artificial intelligence based decision mechanisms strongly depends on selecting appropriate model parameters. This includes, for example, the weights and biases of neural network models, as well as criterion weights in Multiple Attribute Decision Making (MADM) techniques.Accurate parameter tuning is therefore critical for improving prediction accuracy and ensuring that decisions are made with minimal error. Nevertheless, conventional optimization methods may become inefficient when the search space is large and the objective landscape is complex, and they may also suffer from premature convergence to local optima especially in nonlinear or multi-modal problems. Traditional optimization approaches often exhibit inefficiency and premature convergence to local optima when faced with nonlinear, dynamic, or multi-objective problems. To address these limitations, metaheuristic optimization algorithms have gained prominence, offering efficient exploration of large and complex search spaces while avoiding local minima and delivering high quality near optimal solutions within acceptable computational limits. Such algorithms are particularly effective for HO

optimization in heterogeneous networks (HetNets), where multiple performance indicators such as latency, throughput, energy efficiency, and service continuity must be balanced. Metaheuristic algorithms have been adopted as flexible optimization tools capable of handling high dimensional, non-convex, and constrained problems. By combining global search capability with iterative refinement, metaheuristics enhance the exploration of the solution space, and reduce sensitivity to initialization. In practice, they seek parameter settings that minimize or maximize a predefined cost (fitness) function while satisfying any system constraints. Commonly used metaheuristics include simulated annealing, genetic algorithms(GA), particle swarm optimization (PSO), Grey Wolf Optimization(GWO), Mayfly Optimization(MFO), artificial bee colony algorithm (ABC), and ant colony optimization (ACO), in addition to other methods inspired by natural phenomena. Metaheuristic optimization has been applied to numerous network problems, as discussed in[22–25]. A number of studies have specifically applied metaheuristics to handover and network selection problems in HetNets. The work of Goudarzi et al.[25] combined ABC and PSO with Saaty's Analytic Hierarchy Process (AHP) to determine optimal QoS weights in an IEEE 802.21-based cost function, thereby reducing handover delay and unnecessary transitions. Similarly, Al-Gharabally et al.[26] applied PSO to eliminate subjectivity in MADM-based network ranking by automatically tuning attribute weights such as delay, jitter, and packet loss, resulting in more consistent access-network selection. On the other hand, Patil and Math[23] proposed a hybrid GWO–MFO framework for seamless vertical handover that jointly optimizes QoS, energy, and security through a three-phase decision process. More recently, Ezz-Eldien et al.[27] introduced an adaptive vertical handover model that integrates MADM with a hybrid PSOGSA algorithm, incorporating Load Factor (LF) and Score Priority (SP) as control parameters to reduce unnecessary handovers and improve load distribution in 5G-enabled HetNets. In a related direction, Mouhassine and Moughit[28] designed a MOS-based prediction model for VoIP offloading from LTE to Wi-Fi and used GWO to tune deep learning models (MLP and LSTM) within an SDN-based control framework, enhancing QoE estimation and enabling proactive handover management. Beyond handover decision-making, metaheuristic optimization has also been investigated for energy-aware clustering, routing, and localization in wireless and sensor networks. For instance, Zhang et al.[29] showed that ABC based clustering can jointly optimize cluster-head selection and multi-hop routing, significantly reducing energy consumption and extending network lifetime compared with classical schemes. Likewise, improved or hybrid PSO variants (e.g., HICPSO), as introduced by Liu et al[30], have been applied to DV-Hop localization and topology control, achieving higher localization accuracy and better convergence behavior than standard PSO. These studies, together with chaotic Whale Optimization Algorithm (CWOA) based handover strategies for 5G and legacy networks reported by Mannem. Et al[31], reinforce the idea that bio-inspired metaheuristics are well suited to complex, multi-objective wireless networking problems involving QoS/QoE, energy, and mobility. Collectively, prior work demonstrates that metaheuristic-driven optimization provides a robust and adaptive framework for intelligent handover management, improved QoE, and energy-efficient communication across heterogeneous wireless environments. Building on this body of research, our work implements GA and PSO based decision applications inside an SDN controller operating over a secure MPLS core. Both metaheuristics share a common fitness formulation that combines QoS, QoE, and energy metrics, and are triggered when the predicted QoE of video sessions deteriorates, with the unified objective of selecting the most suitable LTE/Wi-Fi access point for each mobile user.

Table 1 presents a comparison of related works, showing for each reference the year, the optimization algorithm used, the key input metrics, the optimized parameters, and the main optimization objective.

3 System model

3.1 Network layout

The considered scenario is a heterogeneous network (HetNet) integrating a home Wi-Fi access network with an LTE macro network to guarantee service continuity during user mobility. The Wi-Fi segment consists of several fixed Access Points ($AP_1, \ldots, AP_5$) deployed at known stationary positions inside a rectangular area, while LTE provides wide-area coverage when Wi-Fi signal conditions degrade. Both access networks are interconnected through a secured MPLS backbone that ensures traffic isolation, controlled routing, and end-to-end QoS enforcement for traffic flows across the heterogeneous infrastructure. A Mobile Host (MH) equipped with Mobile IPv6 (MIPv6) moves within the rectangular area following a mobility model with random positions and speeds, while maintaining an active video streaming session. Table 2 summarizes the main simulation parameters related to the network layout and mobility assumptions considered in this work.

3.2 Modelling for MOS and PSNR prediction

In this work, the main objective is to optimize acces network selection and handover management in a heterogeneous network (HetNet) composed of a home access network and an LTE cellular network. As a first step, the perceived video quality, expressed by the Mean Opinion Score (MOS) and the Peak Signal-to-Noise Ratio (PSNR)[32,35], is predicted in order to characterize the network performance; these predictions are then exploited by a metaheuristic algorithm to select the most suitable access network. To build the training dataset, we first generate MOS time series using the E-model (ITU-T G.107)[33,34]. In this model,

Table 1. Comparison of Prior Studies: Optimization Algorithms and Goals.

References	Year	Algorithms	Key Inputs	Optimized Parameters	Optimization Goal
Goudarzi et al.	2021	ABC + PSO with AHP	QoS criteria (bandwidth, delay, jitter, packet loss, cost)	Weighted cost function for network ranking	Minimize handover delay and unnecessary transitions; select optimal target network
Zhang et al.	2025	ABC, enhanced LEACH-based clustering/routing	Node residual energy, distance to cluster head (CH) and sink, hop count, neighbour density/connectivity, link quality metrics	Cluster-head selection, multi-hop routing paths, and cluster formation structure	Minimize energy consumption and extend network lifetime; maintaining reliable data delivery across sensor nodes
Al-Gharabally et al.	2022	PSO + DIA (MADM)	QoS metrics (delay, jitter, security, packet loss, cost, data rate)	Optimized attribute weights for DIA ranking	Remove subjectivity in MADM; achieve consistent network selection
Patil & Math.	2022	GWO + MFO (hybrid)	QoS, RSS, battery level, security	Network utility and decision score	Achieve seamless VHO; reduce latency and packet loss via three-phase optimization
Ezz-Eldien et al.	2023	PSO–GSA (hybrid) + MADM	Optimized handover weights and decision threshold	Optimized handover weights and decision threshold	Reduce unnecessary handovers (>40%) and improve load balancing in 5G HetNets
Mouhassine & Moughit.	2024	GWO + ML (MLP and LSTM)	LTE/Wi-Fi signal metrics (RSSI, SNIR, MOS samples)	Predicted MOS and optimal AP selection	Enhance QoE prediction and enable proactive VoIP handover decisions via SDN
Lu et al.	2022	PSO + ABC (hybrid) in SDWSN	Node energy, cluster distance, BS trajectory parameters	Cluster-head selection and BS sojourn path	Reduce energy consumption and latency; extend network lifetime
Liu et al.	2024	Hybrid improved compressed particle swarm optimization (HICPSO)	Received signal strength/SINR, available bandwidth, delay/jitter, packet loss, user velocity, and possibly cost/priority weights	Weights and/or thresholds in the handover decision function; ranking/selection of target access technologies or cells	Reduce handover failures and unnecessary handovers while maintaining QoS/QoE and service continuity in multi-RAT environments
Bayrakdar & Çalhan	2021	ACO	Channel bandwidth, interference, PU/SU activity	Spectrum selection and handover path	Minimize spectrum handover delay and interference in CRNs
Mannem et al.	2025	Chaotic Whale Optimization Algorithm (CWOA) for vertical handover	Received signal strength, SINR/SNR, throughput/data rate, delay, jitter, packet-loss-related metrics, user speed	Target-network (RAT) selection and associated decision weights/scoring values in the HO cost function	HO failure probability, ping-pong and unnecessary handovers maximizing user QoS/QoE and effective throughput across 5G and legacy networks
Ours	2026	PSO, GA + MLP-based SDN	QoS metrics, RSSI, energy	QoS and energy efficiency	Minimise energy consumption and maximise QoS; enable proactive video-stream handover decisions via SDN

the transmission rating factor R is computed as

$$R = R_0 - I_s - I_d - I_e + A \tag{1}$$

where R_0 is the basic signal-to-noise ratio, I_s represents impairments that occur simultaneously with the voice signal, I_d accounts for delay-related impairments, I_e models equipment and codec impairments including the effect of packet loss, and A is the advantage factor reflecting the user's increased tolerance in special circumstances (e.g., mobile or satellite communication). Once R is obtained, it is mapped to an estimated MOS through the empirical relation

$$\text{MOS} = 1 + 0.035R + 7 \times 10^{-6} R(R-60)(100-R), \tag{2}$$

Table 2. Network infrastructure components.

Group	Elements or settings
Network area	Rectangular area; fixed Wi-Fi APs ($AP_1, \ldots, AP_5$); LTE macro coverage available
Wi-Fi access network	IEEE 802.11ac
LTE macro network	eNB coverage overlap with Wi-Fi; LTE bandwidth available
Backbone/core	Secure MPLS backbone interconnecting Wi-Fi and LTE
Network entities	SDN/OpenFlow control elements (controller + switches)
Mobile nodes	Number of mobile hosts: 10; MIPv6-enabled; rectangular mobility; speed per segment $v_i \in [v_{\min}, v_{\max}]$; position update every Δt
Traffic	Continuous video streaming
Quality indicators	MOS, PSNR

where $R \in [0, 100]$, with higher values indicating better perceived quality.

In parallel, the PSNR of each received video sequence is computed as an objective measure of distortion. For each frame, the mean squared error (MSE)[35] between the original and reconstructed video is calculated as

$$\mathrm{MSE} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left[I(i,j) - K(i,j) \right]^2, \tag{3}$$

where $I(i,j)$ and $K(i,j)$ denote the pixel intensities of the original and reconstructed images, respectively. The PSNR is then derived as

$$\mathrm{PSNR} = 10 \log_{10} \left(\frac{\mathrm{MAX}_I^2}{\mathrm{MSE}} \right), \tag{4}$$

with MAX_I being the maximum possible pixel value (255 for 8-bit images).

- M, N: frame width and height (number of pixels in each dimension).
- $I(i,j)$: pixel value of the original video at position (i,j).
- $K(i,j)$: pixel value of the received/decoded video at position (i,j).
- MSE: average squared difference between original and received pixels.
- PSNR: Peak Signal-to-Noise Ratio (dB), where higher values indicate better quality.

A higher PSNR value corresponds to lower distortion and better visual quality. For interpretability, PSNR values are mapped to MOS categories as summarised in Table 3. Values above 37 dB correspond to MOS = 5 (excellent), while values below 20 dB correspond to MOS = 1 (bad). Intermediate intervals represent good (MOS = 4), reasonable (MOS = 3), and poor (MOS = 2) quality levels. Both MOS and PSNR time series are used as target outputs for training the neural network. The proposed MLP is a feed forward neural network designed to capture the non-linear relationship between network level

Table 3. Mapping between PSNR and MOS values.

PSNR (dB)	MOS	Video Quality
> 37	5	Excellent
$31 \sim 37$	4	Good
$25 \sim 31$	3	Reasonable
$20 \sim 25$	2	Poor
< 20	1	Bad

QoS indicators and application level QoE metrics[36]. The network input is a four dimensional vector comprising throughput, end-to-end delay, packet loss , and jitter observed during each video session within the Home and LTE HetNet passes them

through a fully connected hidden layer (ReLU), and outputs two continuous QoE estimates: MOS and PSNR. Each hidden neuron implements the perceptron operation :

$$Y_k = f\left(b_k + \sum_{i=1}^{4} x_i w_{ki}\right). \tag{5}$$

where x_i are the inputs, w_{ki} the weights, b_k a bias term, and $f(\cdot)$ is the activation function. ReLU activations are applied in the hidden layer to introduce non-linearity, while linear activations are used at the output layer to produce continuous MOS and PSNR estimates. The perceptron operation is shown in Figure 1.

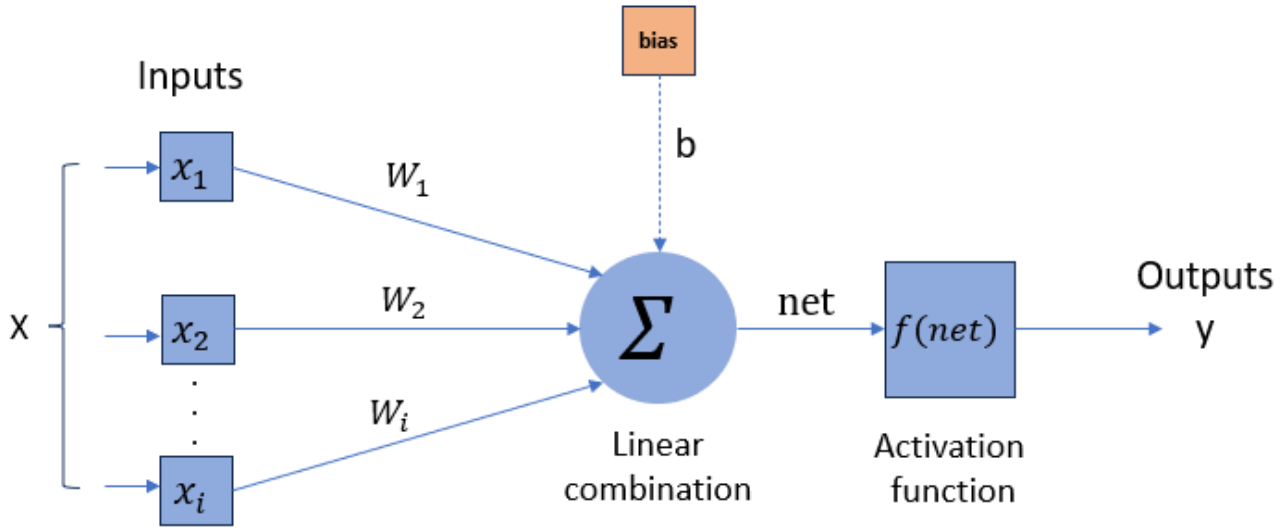


Figure 1. Architecture of perceptron.

To address our task of predicting MOS and PSNR with an MLP architecture, we use the model shown in Figure 2. The inputs $\widetilde{x_1}$, $\widetilde{x_2}$, $\widetilde{x_3}$, and $\widetilde{x_4}$ correspond to the normalized values of Throughput, Packet Loss, Delay, and Jitter, respectively, and the network outputs the estimated MOS and PSNR.

Normalization is crucial to place heterogeneous features on a comparable scale. Raw metrics differ in units and magnitude (e.g., Throughput in Mbps vs. Jitter in ms); without normalization, larger-magnitude features can dominate the optimization, biasing the model and degrading accuracy. By standardizing each feature, the MLP receives balanced inputs and can learn subtle QoS→QoE relationships more effectively. Concretely, if $x \in \mathbb{R}^{N\times 4}$ is the feature matrix with columns $\{x_1 : \text{Throughput}, x_2 : \text{Packet Loss}, x_3 : \text{Delay}, x_4 : \text{Jitter}\}$, we apply the normalization of the z-score per-feature:

$$\widetilde{x_i} = \frac{x_i - \mu_i}{\sigma_i + \varepsilon}, \tag{6}$$

where x_i is the raw value of the characteristic i, and μ_i, σ_i are the mean of the training-set and the standard deviation of that characteristic (with a small $\varepsilon \approx 10^{-6}$ to avoid division by zero). The MLP works with the normalized vector

$$\left[\widetilde{x_1}, \widetilde{x_2}, \widetilde{x_3}, \widetilde{x_4}\right].$$

The proposed NN driven handover assistant that continuously monitors packet level QoS (jitter, delay, packet loss, and throughput) from mobile video streams. After per feature z-score normalization, a lightweight feedforward network maps these four inputs to two QoE indicators, PSNR and MOS, estimated each interval. The controller interprets the predictions against standard quality bands based on Table 3. The resulting NN based handover assistant continuously monitors packet level QoS metrics for ongoing video sessions. At each sampling interval, the normalized QoS vector is fed to the trained MLP, which outputs the predicted PSNR and MOS values. The SDN controller then compares these predicted values with the thresholds defined in Table 3. When a degradation in predicted quality is detected or anticipated, the controller proactively initiates a handover between home and LTE networks or selects a better access point, thereby maintaining the desired video quality with minimal signaling overhead.

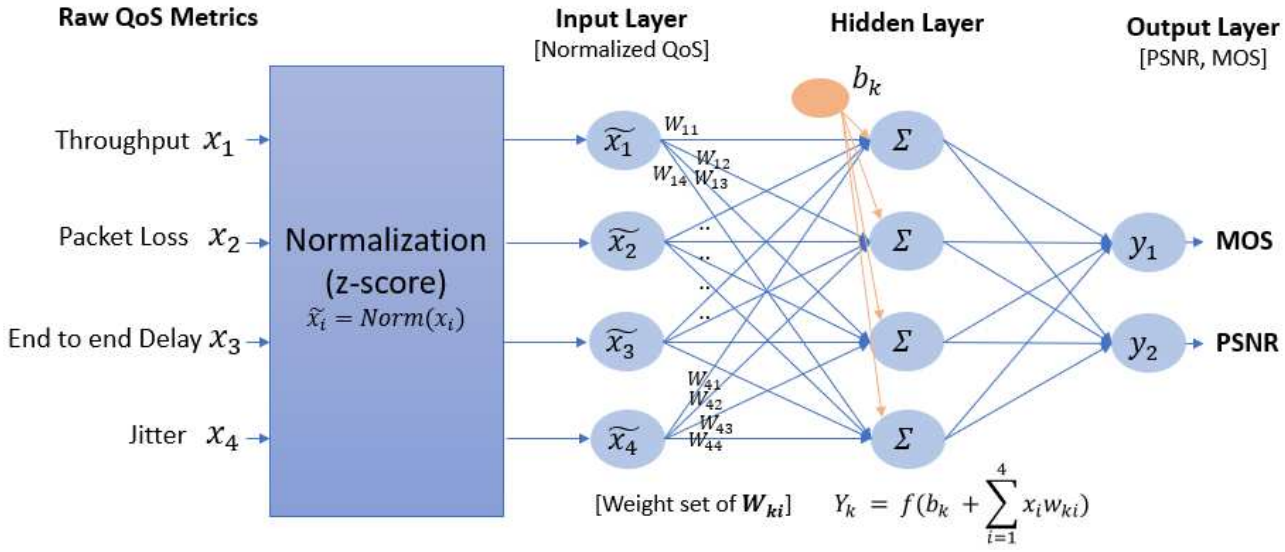


Figure 2. Neural network (MLP) for QoE prediction.

3.3 QoS to QoE Prediction Model

When degradation is detected or anticipated, it proactively triggers a transfer between LTE and HOME to the best available AP to preserve the video quality of the target, such as $\mathrm{AP}_i \in A = \{\mathrm{AP}_1, \ldots, \mathrm{AP}_5, \mathrm{LTE}\}$. This design turns passive QoS sensing into fast, model-guided decisions, enabling timely, per-flow mobility control without intrusive probing and with minimal overhead.

To construct the database used for training and testing our model, we performed simulations using OMNeT++[1] with the INET framework[2]. The simulated network consists of Wi-Fi access points, an LTE cellular network, a Video Stream server, and ten mobile nodes $h_i \in H = \{h_1, \ldots, h_{10}\}$. The mobile nodes move according to a rectangular mobility model, where for each movement segment, a random destination and speed are selected. Once the waiting time has elapsed, the algorithm recalculates a new position and continues the motion. This setup allows covering the full range of MOS 1 to 5 and PSNR values according to Table 4.

The main QoS metrics (Q_i) delay, jitter, packet loss, and throughput were calculated using the following mathematical expressions:

Delay:

$$D_i = (t_i - t_{i-1}) \times 1000 \ [\mathrm{ms}] \tag{7}$$

where t_i represents the reception time of the i^{th} packet.

Jitter:

$$J_i = J_{i-1} + \frac{|D_i - D_{i-1}| - J_{i-1}}{16} \tag{8}$$

which represents the smoothed variation of inter-packet delay.

Packet Loss:

$$\mathrm{PL}_i = \frac{L}{N} \times 100 \tag{9}$$

where L is the number of lost packets and N the total number of received packets.

Throughput:

$$\mathrm{Th}_i = \frac{S_i \times 8}{(t_i - t_{i-1}) \times 1000} \ [\mathrm{kbps}] \tag{10}$$

[1] https://omnetpp.org
[2] https://inet.omnetpp.org

where S_i is the packet size in bytes.

In our simulator, we implement a controller application that manages OpenFlow switches and drives adaptive client handovers using a learned QoS model[37]. On startup, the controller binds a UDP packet, discovers switches from incoming OpenFlow HELLO messages (tracking each switch's address and port), and can issue FEATURES_REQUEST/FEATURES_REPLY exchanges. Incoming PACKET_IN messages are either forwarded with PACKET_OUT (specifying the selected output port) or explicitly dropped via a PACKET_OUT to OFPP_ANY, while counters for packet-ins, packet-outs, flooded packets, and dropped packets are maintained.

The controller uses a configurable service time scheduler and an internal message queue to serialize work when parallel processing is disabled. It records the number of packets per second and computes a time-weighted average queue size, which allows it to capture the transient load at the controller. All simulations are carried out over a core MPLS network secured by a machine-learning-based intrusion detection and prevention system (ML-IDPS), which continuously monitors traffic and enforces security policies during the optimization and handover procedures.

In the proposed framework, QoS metrics module D_i, J_i, PL_i, and Th_i are collected at the UE from the UDP video stream using `getQoSMetrics()`. The UE executes an embedded MLP model to predict QoE indicators (MOS and PSNR), then encodes these values into a discrete fitness score F_i using the rule-based `computeFitness()` function.

These four values are then assembled into a 1×4 feature vector and normalized before being passed to a neural network model. In the implementation, normalization is performed by subtracting a pre-computed mean and dividing by a standard deviation for each QoS metric (using the `means[]` and `stds[]` arrays in the controller code). This ensures that all input features are on a comparable scale and match the distribution seen during training.

The normalized QoS vector is then fed into an ONNX neural network that is loaded at runtime via OpenCV DNN[39] (e.g., using `cv::dnn::readNetFromONNX("qos_predictor.onnx")`). This ONNX file referred to here as `QoS_metrics.onnx` encodes a regression model that was trained offline on a dataset of measured QoS indicators and their corresponding subjective or objective quality scores (MOS and PSNR). Given a normalized input vector, the network outputs two continuous QoE predictions: let M be the rounded $\widehat{\mathrm{MOS}}$ prediction and P the rounded $\widehat{\mathrm{PSNR}}$ prediction for a given host. In other words, during the training phase, many samples of the form input: $(D_i, J_i, \mathrm{PL}_i, \mathrm{Th}_i)$, and labels: (M,P), were used to learn a mapping from QoS to QoE, and the resulting trained weights were exported to the ONNX file. At runtime, the controller only performs inference using this pre-trained model.

The raw predictions are then discretized (rounded) and mapped into five QoE classes: poor (score 1), low (score 2), reasonable (score 3), good (score 4), and excellent (score 5). A score of 0 is reserved for pathological or invalid cases.

After normalization of Q_i, the QoS/QoE model produces the predicted QoE pair:

$$f_{\mathrm{QoE}}(Q_i) = (M,P).$$

These values are converted into a discrete fitness score, as presented in Table 4:

$$F_i = F(M,P) \in \{0,1,2,3,4,5\},$$

Table 4. Quality levels and the corresponding fitness scores.

PSNR (dB)	MOS	Video Quality	Fitness Score
> 37	5	Excellent	5
$31 \sim 37$	4	Good	4
$25 \sim 31$	3	Reasonable	3
$20 \sim 25$	2	Poor	2
< 20	1	Bad	1

The computed fitness score is sent to the SDN controller through periodic reports or OpenFlow notification events. Based on predefined thresholds, the controller decides whether to maintain the current association or trigger a GA/PSO optimization process to rank candidate access points and select the best AP for handover execution.

The flowchart in Figure 3 illustrates the internal processing chain executed by the SDN controller before the metaheuristic optimization stage. For each mobile host h_i, the controller first collects a measurement vector Q_i describing its current network conditions. This vector is fed to the MLP-based QoE model to predict the corresponding MOS and PSNR values, which are then combined with QoS indicators and encoded into a discrete fitness score $F_i \in \{0,1,2,3,4,5\}$. The resulting fitness values and thresholds T are finally provided to the PSO/GA module, which exploits them to select the most suitable access network.

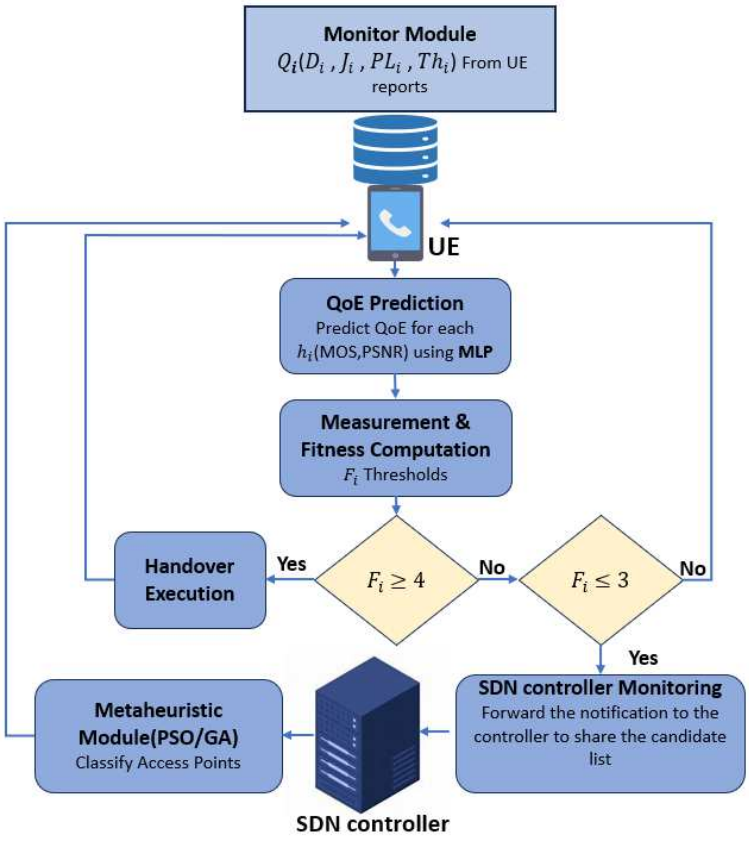


Figure 3. Process Flow of QoE Prediction and Metaheuristic Access Point Selection.

3.4 Metaheuristic handover optimization in secure LTE/Wi-Fi HetNets based MPLS networks

In the proposed architecture, the handover problem in a heterogeneous LTE/Wi-Fi access network is formulated as a multi-objective optimization task jointly executed by mobile nodes and an SDN controller running on a secure MPLS core[?]. Wi-Fi and LTE access points are statically deployed in fixed positions, while mobile hosts move within the coverage area and periodically measure their local QoS indicators (end-to-end delay, jitter, packet loss rate and throughput), which are reported to an MLP model. Inside the QoS/QoE model, these measurements are first mapped into five QoE classes: poor (score 1), low (score 2), reasonable (score 3), good (score 4), and excellent (score 5). The resulting QoE score is then combined with the raw QoS metrics and the UE energy consumption to form a global fitness value for each possible association between a host and a candidate access point (AP). When the estimated QoE of a video session degrades (the fitness score falls below a predefined threshold), the SDN controller triggers a metaheuristic search procedure to look for a better AP among the fixed LTE/Wi-Fi nodes. Two alternative search engines are implemented as SDN controller decision applications: a Genetic Algorithm (GA) module and a Particle Swarm Optimization (PSO) module. Both applications operate on the same fitness function and measurement set, and differ only in the way they explore the space of candidate APs. Their common objective is to select, for every mobile host, the AP (Wi-Fi or LTE) that maximizes user perceived quality while keeping energy usage low, under the protection of an ML-based intrusion detection and prevention system (ML-IDPS) deployed in the MPLS core.

In the proposed model, the GA/PSO is implemented in the SDN controller to select the best Access Point (AP) for a mobile host based on predicted QoE (MOS, PSNR) from the MLP model, signal strength (RSSI), and energy consumption of the mobile node. The controller periodically evaluates the quality of every host–AP association and steers hosts toward the access point that offers the best perceived video quality. At each evaluation, the controller first queries the client modules via `getQoSMetrics()` for each host the current QoS measurements: D_i, J_i, PL_i, and Th_i. These four values are assembled into a feature vector and normalized before being passed to the QoS/QoE model, which returns predicted MOS and PSNR. The controller then applies the rule-based `computeFitness` function to convert these two values into a discrete fitness score between 0 and 5. Two thresholds are used to control the handover logic:

- When the fitness score falls below 3, the mobile node sends a request to the SDN controller, which then prepares a ranked list of candidate access points (APs) with better expected quality and triggers a handover procedure.

- When the fitness score reaches 4 or 5, the controller forces the UE to remain attached to the current AP, which is at that moment considered the best AP.

The controller builds an initial population of chromosomes from A_i^{cand}. Each individual encodes a candidate handover configuration $\{\text{AP}_1,\ldots,\text{AP}_5,\text{LTE}\}$ and may include tunable parameters (e.g., w_1, w_2, w_3, thresholds), initialized randomly within allowed bounds. The fitness score $F(M,P)$ is defined as:

$$F(M,P)=\begin{cases}5, & P>37 \text{ and } M\geq 5,\\ 4, & 31\leq P\leq 37 \text{ and } M\geq 4,\\ 3, & 25\leq P<31 \text{ and } M\geq 3,\\ 2, & 20\leq P<25 \text{ and } M\geq 2,\\ 1, & 1\leq P<20 \text{ and } M\geq 1,\\ 0, & \text{otherwise.}\end{cases} \tag{11}$$

A schematic overview of this GA/PSO-assisted handover framework in the secure MPLS-based LTE/Wi-Fi HetNet is depicted in Fig. 4, while the main symbols and notations used in the formulation are summarized in Table 5.

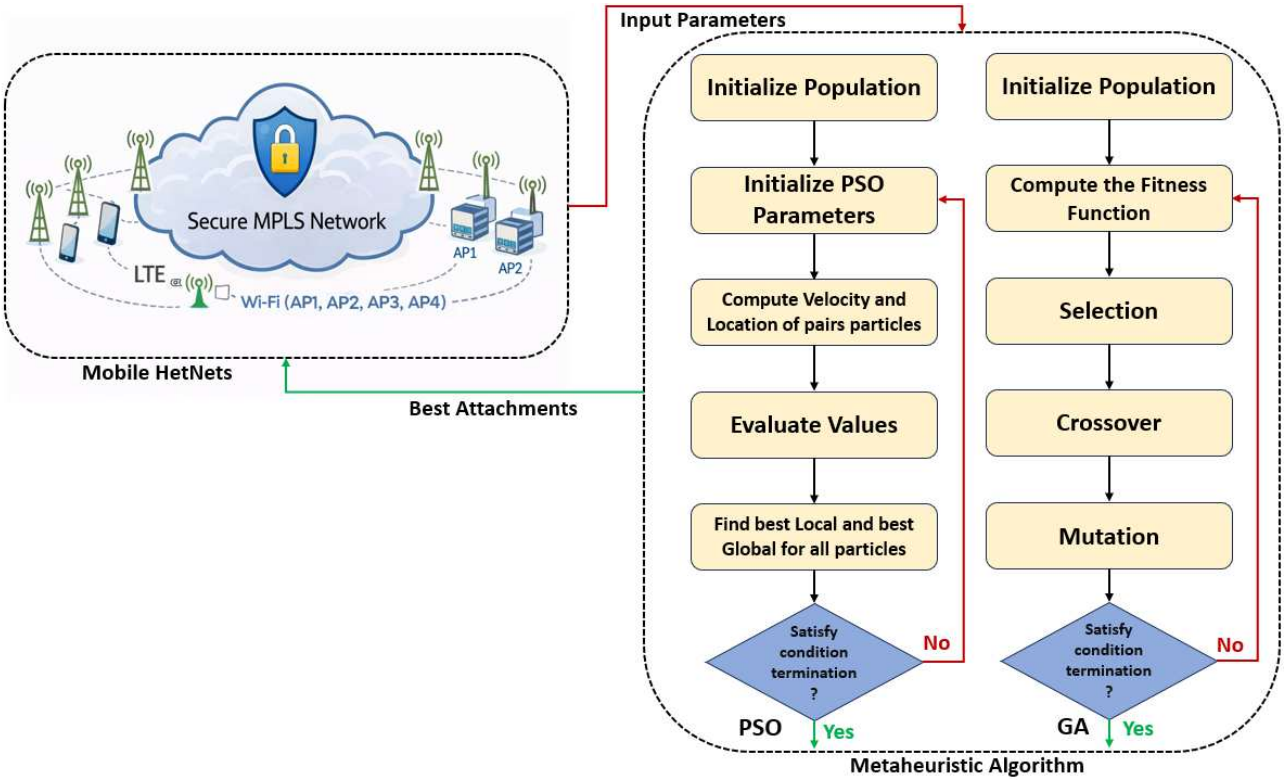


Figure 4. Overall flow of PSO and GA for attachment decision.

- **PSO:** Each particle represents an AP choice for a host; its quality is F_{ij}. PSO updates Pbest and Gbest by maximising F_{ij}.
- **GA:** Each individual encodes an AP assignment; selection, crossover, and mutation are driven by the same fitness F_{ij}. Thus, GA and PSO optimise the same objective function, but using different search strategies.

This common representation allows the GA and PSO based decision applications to operate on the same symbol set and objective, differing only in the search strategy they use to explore the fixed LTE/Wi-Fi access points AP_j. The SDN controller thus becomes a generic metaheuristic engine running over a secure MPLS core, with the ML-IDPS ensuring that only legitimate traffic and trustworthy measurements are used during optimization. In the following subsections, we detail how the GA module and the PSO module instantiate this framework, specifying their update rules, genetic or swarm operators, and their roles in

Table 5. Notation and symbol descriptions.

Symbol	Description
$H = \{h_1, \ldots, h_{10}\}$	Set of mobile hosts (UEs)
$A = \{\mathrm{AP}_1, \ldots, \mathrm{AP}_5, \mathrm{LTE}\}$	Set of candidate access networks (Wi-Fi APs and LTE)
D_i	End-to-end delay measured for host h_i
J_i	Jitter measured for host h_i
PL_i	Packet loss rate for host h_i
Th_i	Throughput for host h_i
$Q_i = [D_i, J_i, \mathrm{PL}_i, \mathrm{Th}_i]$	QoS vector of host h_i
F_i	Discrete fitness score
E_{ij}	Energy consumption of host h_i when attached to AP_j
RS_j	Received signal strength (RSSI) at host h_i from AP_j
$G_i(\mathrm{AP}_j)$	GA/PSO multi-criteria fitness of associating host h_i with AP_j
w_1, w_2, w_3	Weights for QoE, RSSI and energy terms in the fitness function
$\mathrm{AP}_i^{\mathrm{curr}}$	Current serving AP of host h_i
AP_i^*	AP selected for host h_i by GA/PSO optimization
$\mathbf{x}_i^{(p)}$	Position (candidate AP assignment) of PSO particle at iteration t
$\mathbf{v}_i^{(p)}$	Velocity of PSO particle at iteration t
$v_i(t)$	Mobility speed of host h_i at time t
$U(-1,1)$	Uniform random variable in the interval $[-1,1]$ used for mobility perturbation
MPLS	Multi Protocol Label Switching core network
ML-IDPS	Machine Learning Intrusion Detection and Prevention System securing the MPLS core

Table 6. Optimization goals of the handover algorithms.

Symbol	Metric	Description	Objective
Q	QoS	Predicted video quality	Maximize
RS	RSSI	Received Signal Strength	Maximize
E	Energy Consumption	Transmission, scanning and switching	Minimize

minimizing energy usage while maximizing user perceived video quality. The two algorithms optimize the handover decision by maximizing overall user experience and minimizing energy use, as presented in Table 6.

For both GA and PSO, each candidate AP assignment is evaluated by a single scalar fitness combining all QoS and energy terms. We first normalize each raw metric into $[0,1]$. Let m be a generic metric with minimum and maximum bounds $m_{\min}$ and $m_{\max}$. We define:

- if m must be maximized (RSSI, throughput):

$$\widetilde{m} = \frac{m - m_{\min}}{m_{\max} - m_{\min}} \tag{12}$$

- if m must be minimized (energy, delay, jitter, packet loss):

$$\widetilde{m} = 1 - \frac{m - m_{\min}}{m_{\max} - m_{\min}} \tag{13}$$

For host h_i attached to AP_j we define the normalized metrics E_{ij}, RS_{ij}, J_{ij}, D_{ij}, PL_{ij}, $\mathrm{Th}_{ij} \in [0,1]$.

3.4.1 GA Based fitness and handover decision logic

In the proposed framework, the Genetic Algorithm (GA) is used as a QoE-driven optimization engine that runs inside the SDN controller. The GA operates on candidate host–AP associations of the form (h_i, AP_j). Each gene in a chromosome represents a

specific (h_i, AP_j) pair, while a chromosome encodes a complete assignment of all active hosts to their serving access points. In this way, a single chromosome captures a global network configuration, and the GA can evaluate not only the quality of individual handovers but also the overall balance of associations across the heterogeneous LTE/Wi-Fi infrastructure.

For each candidate pair (h_i, AP_j), the SDN controller evaluates the expected quality using the information reported by the host. The host-side MLP model first predicts the QoE metrics MOS and PSNR from locally measured QoS indicators (end-to-end delay, jitter, packet loss rate, and throughput) extracted from the UDP video stream. These values are mapped into a discrete QoE fitness score $F_i \in \{0,1,2,3,4,5\}$ through the `computeFitness()` function. Together with this QoE score, the controller also considers the corresponding QoS measurements and the estimated UE energy consumption if h_i were attached to AP_j. All these components are merged into a fitness value associated with the gene (h_i, AP_j). During GA evolution, standard operators such as selection, crossover, and mutation explore different combinations of these genes, producing new chromosomes (candidate global assignments). After several generations, the GA converges toward the chromosome with the highest overall fitness, which defines the final set of (h_i, AP_j) associations used by the controller to perform or avoid handovers.

The GA module is not continuously active; instead, it is triggered adaptively whenever the discrete QoE fitness score of a host falls below a predefined acceptable level. Two main situations are distinguished:

- **Case 1: High quality $F(M,P) \in [4,5]$ (Good to Excellent).**

  When the QoE fitness score derived from the predicted MOS and PSNR satisfies $F(M,P) \in [4,5]$, the current association is considered good or excellent. In this case, the main objective is stability rather than aggressive re-optimization. If the global variable `bestFit` is still empty, the controller records the host's current access point $\mathrm{AP}_j^{\mathrm{curr}}$ and stores it as the best choice, denoted by $\mathrm{AP}_{\mathrm{bestFit}}$. For all evaluated hosts in this high-quality situation, the controller then applies a GA-style "selection" step at the association level, forcing them to remain attached to this high-quality AP:

  $$\mathrm{AP}_{\mathrm{host}} \leftarrow \mathrm{AP}_{\mathrm{bestFit}} \qquad \text{and} \qquad \mathrm{AP}_j(t+1) \leftarrow \mathrm{AP}_j^{\mathrm{curr}}. \tag{14}$$

  This means that if the connection already offers good or excellent QoE, the network preserves the current association and avoids unnecessary handovers.

  To encourage a limited form of exploration around this good operating point, the controller slightly perturbs the mobility speed of the hosts. In the implementation, the new speed is computed as:

  $$v_i(t+1) = v_i(t) + |U(-1,1)|, \tag{15}$$

  where $U(-1,1)$ is a random variable sampled uniformly in the interval $[-1,1]$. This small random variation plays the role of a mobility-level mutation operator, allowing hosts to experience slightly different radio conditions around the same AP. From the GA perspective, quality is already excellent, but the system still samples nearby positions to confirm the robustness of the current solution. At the same time, the controller periodically generates lightweight "fitness" messages (denoted as `QoSPacket`) that encapsulate the host's energy consumption and received signal strength (RSSI). These messages are processed by the `handleHandover` routine, which compares pre- and post-interval energy and RSSI values. If these indicators evolve as expected and QoE remains within the good/excellent range, the association is confirmed and no handover is triggered; the controller simply continues monitoring and iterating in the next evaluation period.

- **Case 2: Low quality $F(M,P) \in [1,3]$ (Bad to Reasonable).**

  When the QoE fitness score drops to 3 or below, i.e., $F(M,P) \in [1,3]$, the current association is considered unsatisfactory (bad to at best reasonable quality). In this situation, the host h_i signals to the SDN controller that its current link is not acceptable and that a handover should be considered. The controller then prepares a set of candidate access points for that host, denoted by $A_i^{\mathrm{cand}} \subseteq A$, where A is the set of all available LTE/Wi-Fi APs in the system.

  For each candidate AP $\mathrm{AP}_j \in A_i^{\mathrm{cand}}$, the controller activates the GA engine and evaluates a composite objective function:

  $$G_i(\mathrm{AP}_j) = w_1 F_{ij} + w_2 \mathrm{RS}_j + w_3 (1 - E_{ij}), \tag{16}$$

  where F_{ij} is the expected QoE score if h_i attaches to AP_j, RS_j is the received signal strength indicator (RSSI), E_{ij} is the estimated UE energy consumption over evaluation window T if it attaches to AP_j, and w_1, w_2, w_3 are weighting factors controlling trade-offs between QoE, signal strength, and energy efficiency, with the constraint $w_1 + w_2 + w_3 = 1$.

  Both RSSI and energy consumption are evaluated from the host's perspective, conditioned on attaching to AP_j. The GA uses this composite score $G_i(\mathrm{AP}_j)$ as the fitness value for each candidate gene. Through iterative selection, crossover, and mutation, the GA searches for the AP that maximizes this objective. The optimal AP for host h_i is selected as:

  $$\mathrm{AP}_j^* = \arg\max_{\mathrm{AP}_j \in A} G_i(\mathrm{AP}_j).$$

If $G_i(\mathrm{AP}_j^*)$ satisfies the QoE, RSSI, and energy constraints, the controller triggers a handover from the current AP to AP_j^*. If no candidate access point in A_i^{cand} satisfies these conditions (i.e., there is no "best" AP that can bring a real improvement according to the composite score), the controller activates a fallback mechanism and switches the host to the LTE network, $\mathrm{AP}^* = \mathrm{LTE}$, thus ensuring that the UE remains connected even in the absence of a suitable Wi-Fi AP.

If no candidate AP $\mathrm{AP}_j \in A_i^{\mathrm{cand}}$ satisfies these conditions (i.e., no "best" AP can be found that improves the composite score and respects the energy/RSSI constraints), the controller triggers a fallback mechanism and switches the host to the LTE network, $\mathrm{AP}^* = \mathrm{LTE}$, ensuring that the UE remains connected even when no suitable Wi-Fi AP is available.

The association update rule can be summarized as:

$$\mathrm{AP}_j(t+1) = \begin{cases} \mathrm{AP}_j(t), & \text{if } F \geq 4 \text{ (keep current AP)}, \\ \arg\max_{\mathrm{AP}_j \in A} G_i(\mathrm{AP}_j), & \text{if } F \leq 3 \text{ (GA based reassignment)}. \end{cases} \tag{17}$$

For each selected candidate, the GA not only maximizes the composite function, but also considers stability. Before confirming the handover, the controller takes a pre-handover snapshot of the host's energy consumption and RSSI, performs a tentative handover to the GA-selected AP, and then re-measures these quantities over the evaluation window. Only if QoE is improved (or at least not degraded) and the post-handover energy/RSSI remain within acceptable bounds is the new AP confirmed. Otherwise, the host remains attached to its previous AP, and the GA either explores other candidates or opts for the LTE fallback.

Figure 5 illustrates the GA based handover decision process, where host-side MLP QoE estimates are converted into fitness scores and used by the controller to select the best AP.

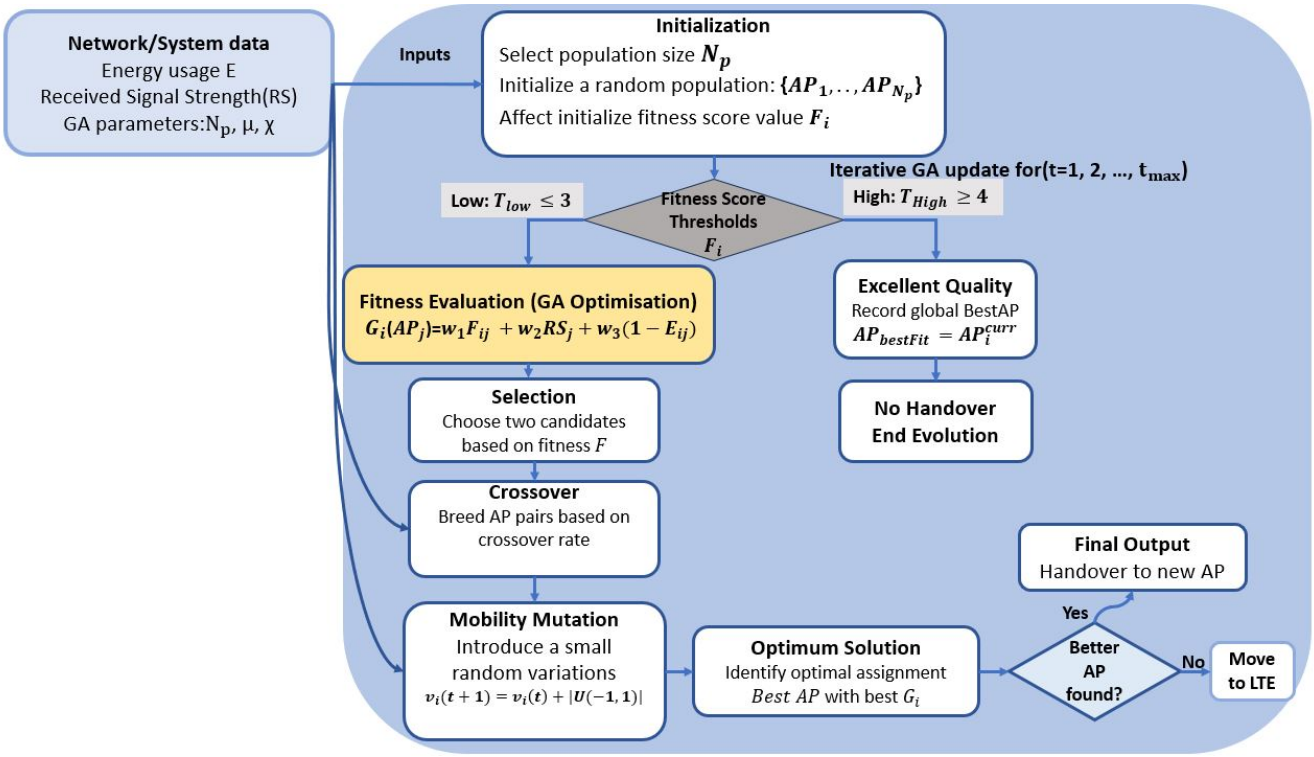


Figure 5. Genetic Algorithm enabled module running on the controller App.

3.4.2 PSO based Multi-Metric fitness and handover decision logic

In addition to GA based decision logic, the SDN controller implements a Particle Swarm Optimization (PSO) engine to refine access point selection for mobile hosts in the heterogeneous LTE/Wi-Fi environment. The PSO-based controller uses the same measurement framework as the GA module: fixed Wi-Fi/LTE access points, mobile hosts moving according to a rectangular mobility model, and a secure MPLS core protected by the ML-IDPS. The main idea is to treat each possible host–AP association as a candidate "solution" and use PSO to search, among all fixed APs, for the one that jointly optimizes energy consumption and QoS related indicators.

The PSO based controller extends the previous logic by defining a continuous fitness function over a richer set of metrics and treating each candidate AP assignment as a particle in the search space. All APs are static, while each mobile host moves according to a rectangular mobility pattern (`RectangleMobility` in OMNeT++), periodically changing its position but always remaining within the coverage of at least one AP. For every host–AP pair (h_i, AP_j), the controller is able to measure or estimate metrics $(F_{ij}, E_{ij}, \mathrm{RS}_j)$.

In the PSO-based controller, each particle encodes a candidate access point (AP) choice for a given host. The position of particle p for host h_i is defined as

$$x_i^{(p)} \in \{1, \ldots, K, \mathrm{LTE}\}, \tag{18}$$

where K denotes the number of available Wi-Fi access points, and LTE represents the cellular attachment option.

At the beginning of each optimization window, the controller creates a swarm of particles for each host h_i and randomly initializes the position and velocity of every particle, i.e., $x_i^{(p)}$ and $v_i^{(p)}$. For each particle p, the controller evaluates the candidate association by attaching (or virtually mapping) h_i to the access point indicated by $x_i^{(p)}$, then collecting the required metrics $\{F_{ij}, E_{ij}, \mathrm{RS}_j\}$ and computing the initial particle fitness $F_{ij}^{(p)}$. In addition, the personal best of each particle is initialized to its current state, while the global best for host h_i is selected as the best personal best among all particles.

- **Personal best value and position for each particle:**

$$pbest_i^{(p)} = F_{ij}^{(p)}, \qquad x_{i,pbest}^{(p)} = x_i^{(p)}. \tag{19}$$

- **Global best value and position among all particles of host h_i:**

$$gbest_i = \max_p \; pbest_i^{(p)}, \qquad x_{i,gbest} = x_{i,pbest}^{(p^\star)}, \tag{20}$$

where

$$p^\star = \arg\max_p \; pbest_i^{(p)}. \tag{21}$$

The APs are fixed and hosts move in rectangular paths, the set of candidate AP indices is static, but the metric values associated with each index evolve with time.

The controller then runs PSO for a maximum of $T_{\max}$ iterations (or until convergence). At each iteration $t = 1, 2, 3, \ldots, T_{\max}$, and for each particle p associated with host h_i, the following steps are performed:

Metric extraction and fitness evaluation: The controller attaches h_i to the access point indicated by $x_i^{(p)}(t)$ (or virtually evaluates this association), collects the current metrics, normalizes them, and computes the particle fitness as

$$F_{ij}^{(p)}(t) = F_{ij}(F_{ij}(t), \mathrm{RS}_j(t), E_{ij}(t)). \tag{22}$$

Update personal and global best:

$$\text{if } F_{ij}^{(p)}(t) > pbest_i^{(p)} \text{ then } pbest_i^{(p)} \leftarrow F_{ij}^{(p)}(t), \qquad x_{i,pbest}^{(p)} \leftarrow x_i^{(p)}(t), \tag{23}$$

$$\text{if } F_{ij}^{(p)}(t) > gbest_i \text{ then } gbest_i \leftarrow F_{ij}^{(p)}(t), \qquad x_{i,gbest} \leftarrow x_i^{(p)}(t). \tag{24}$$

Velocity update (cognitive + social terms):

$$v_i^{(p)}(t+1) = \omega\, v_i^{(p)}(t) + c_1 r_1 \left(x_{i,pbest}^{(p)} - x_i^{(p)}(t)\right) + c_2 r_2 \left(x_{i,gbest} - x_i^{(p)}(t)\right), \tag{25}$$

where ω is the inertia weight, c_1 and c_2 are acceleration coefficients, and $r_1, r_2 \sim \mathscr{U}(0,1)$ are independent random numbers.

Position update and projection to valid AP indices:

$$x_i^{(p)}(t+1) = \Pi_{\mathscr{A}} \left(x_i^{(p)}(t) + v_i^{(p)}(t+1) \right), \tag{26}$$

where $\Pi_{\mathscr{A}}(\cdot)$ denotes the projection operator onto the set of valid AP indices $\mathscr{A}$ (including LTE).

where $\Pi_{\mathscr{A}}(\cdot)$ rounds and clips the value to the discrete set of valid AP indices $\{1,\ldots,K,\text{LTE}\}$.

The hosts continue their rectangular movement while PSO iterates, the swarm dynamically tracks spatial variations in QoS and progressively converges toward access points that provide strong signal conditions, low energy consumption, and favorable delay, jitter, and packet loss characteristics.

After the PSO loop terminates, the optimal access point for host h_i is given by the global best position:

$$AP_i^* = AP_{x_{i,gbest}}. \tag{27}$$

If AP_i^* differs from the current access point, the SDN controller triggers a handover by instructing the management module of h_i to update its association:

$$AP_i(t+1) \leftarrow AP_i^*. \tag{28}$$

In OMNeT++, this operation is performed by calling the station management component (e.g., `Ieee80211MgmtSTA::updateAP`), while access points remain fixed and only the host's association state changes.

Figure 6 summarizes the above procedure. The Initialization block corresponds to swarm creation and the computation of the initial fitness values. The Iterative PSO update block groups metric extraction, fitness evaluation, the personal/global best update rules, and the velocity/position update operations. Finally, the Output block represents the selected access point AP_i^* and the corresponding handover commands issued by the SDN controller.

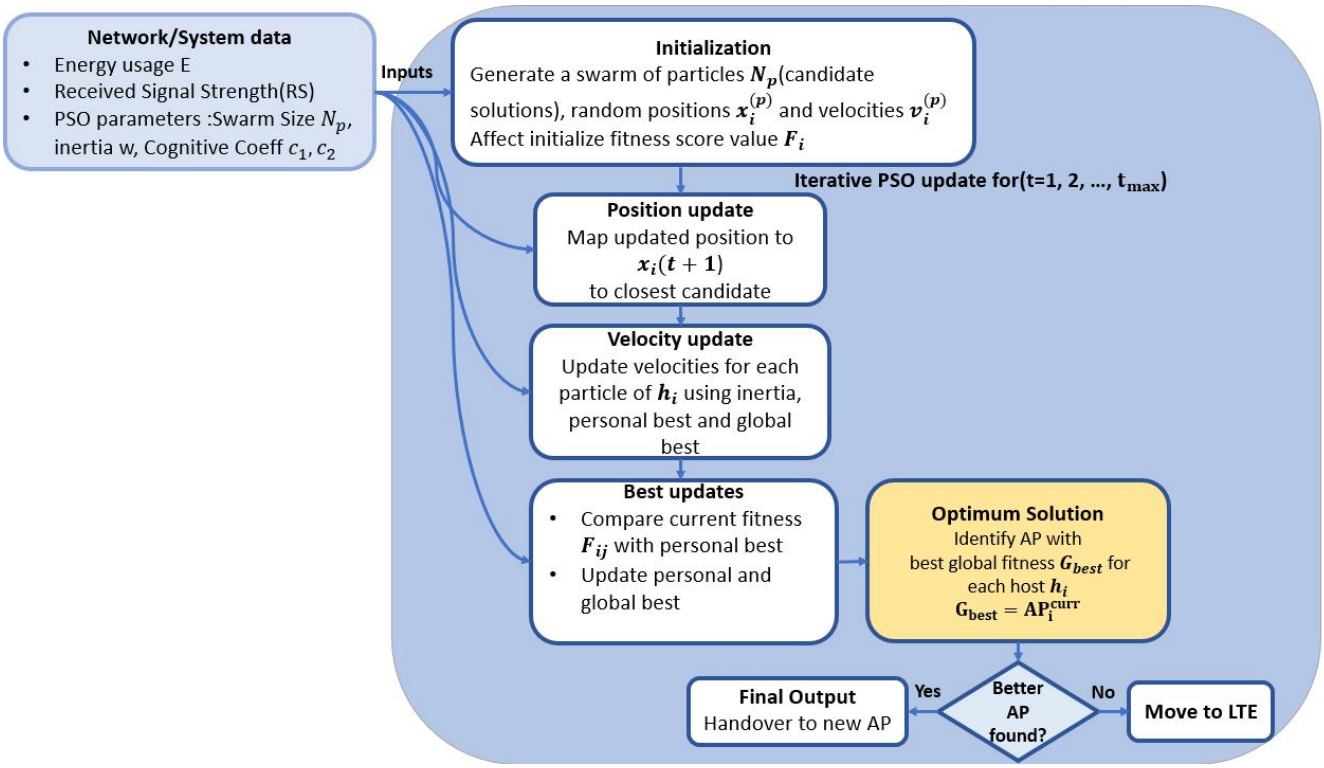


Figure 6. Particle swarm optimization algorithm enabled module running on the controller App.

4 Results and discussion

Quality of service metrics and energy consumption are among the most important indicators for assessing network performance, especially in real-time communication services such as Voice over IP (VoIP) and video streaming. In the suggested QoE-aware framework, the reduction of packet loss is more evident when the MOS/PSNR prediction of the MLP model is combined with intelligent handover decisions. Metaheuristic optimization techniques are particularly useful because they help choose the best network attachment option by exploring many possible choices and avoiding handover decisions that are not optimal. The GA and PSO methods achieve efficient convergence by updating solutions based on the collective intelligence of a group.

4.1 Packet loss

The packet loss rate is a key performance metric in heterogeneous networks, especially for real-time multimedia applications such as video streaming, as it directly affects both QoS and QoE. It represents the percentage of transmitted packets that do not reach the destination due to different factors. In video streaming services, packet loss has a direct impact on QoS and QoE, as missing packets can cause frame drops, video freezing, interruptions, and a noticeable reduction in visual quality.

Figure 7 shows how the average packet loss rate changed over time with GA and PSO based strategies. This shows that using metaheuristic methods for handover optimization leads to more stable transmission and less packet loss compared to traditional handover management methods that rely on the RSSI indicator.

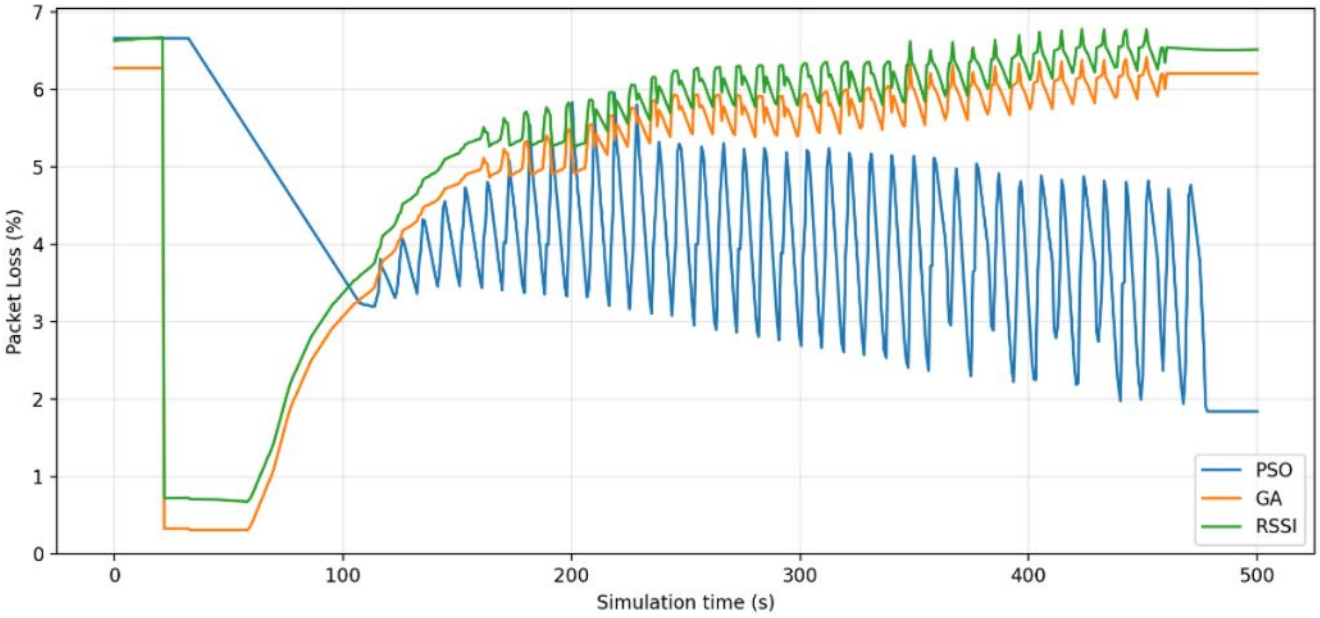


Figure 7. Comparison of average packet loss over time.

At the beginning of the simulation, packet loss remains relatively low, which indicates stable connectivity and favorable radio conditions before mobility and vertical handover effects become significant. After this initial phase, packet loss increases progressively as the UE starts moving and the network becomes more dynamic. From approximately 100 s, the curves show clear performance differences between the three strategies. The RSSI-based approach maintains the highest packet loss level, reflecting the limitations of relying only on signal strength for handover decisions. The GA-based strategy achieves better performance than RSSI; however, it still presents noticeable oscillations and remains at a relatively higher packet loss level during most of the simulation. In contrast, the PSO-based strategy consistently provides the lowest packet loss rate, with smaller variations over time, demonstrating more reliable handover optimization and improved packet delivery stability.

Overall, the results confirm that PSO outperforms GA and RSSI in minimizing packet loss throughout the simulation period. This improvement enhances network QoS and contributes to better QoE for real-time video streaming, supporting higher predicted MOS/PSNR values under mobility conditions.

4.2 Jitter

Jitter is the variation in the time it takes packets to travel from the sender to the receiver. In video streaming and real-time video communication, packets should arrive at a steady and consistent rate, so high jitter can make the video and audio feel unstable, causing playback, or short freezes. To reduce these effects, applications often use a jitter buffer to smooth out packet arrival times, but if jitter becomes too large, it can still lead to noticeable quality drops and delays.

Figure 8 presents the evolution of jitter (ms) over simulation time when applying two metaheuristic-based handover optimization strategies: PSO and GA. At the beginning of the simulation (0–50 s), jitter remains relatively low, reflecting stable transmission conditions before mobility and handover dynamics become significant. As the UE starts moving and handover operations occur more frequently, jitter increases rapidly and reaches its maximum values around 100–150 s, with peaks close to 5 ms. This transient period highlights the impact of mobility and network switching on delay variation. After this phase, both curves show a gradual decrease in jitter, indicating that the network becomes more stable and the handover selection process adapts to the mobility conditions. From approximately 200 s onward, jitter continues to decline with periodic oscillations due to ongoing mobility. In the final interval (400–500 s), jitter values remain lower and more stable, demonstrating improved delay

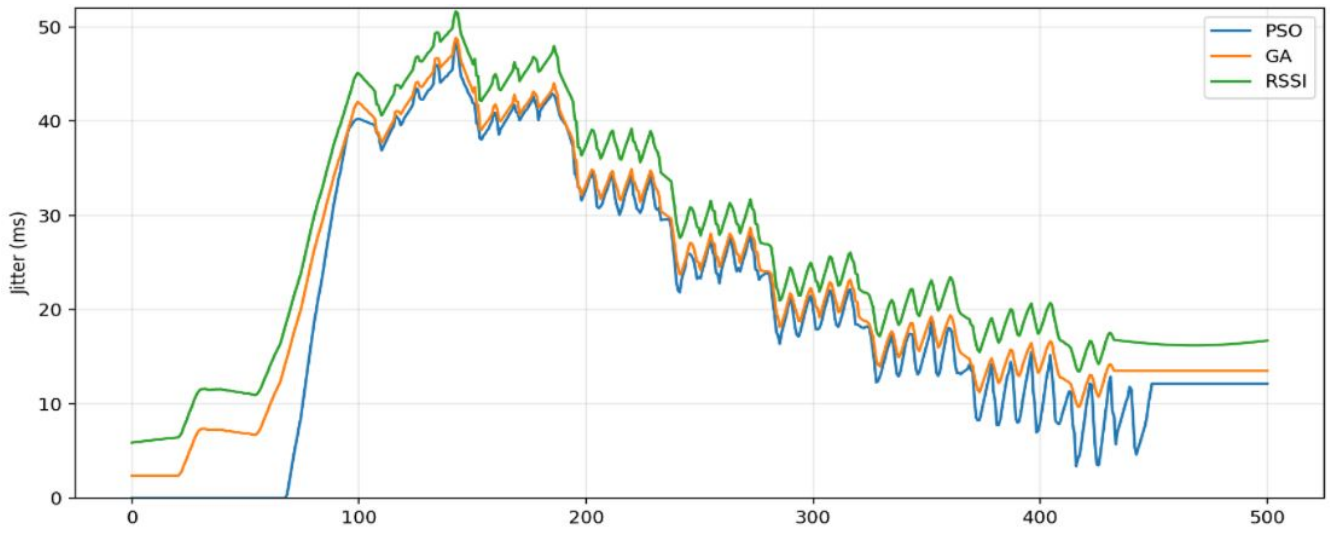


Figure 8. Comparison of average jitter over time.

consistency during video transmission. Overall, the figure confirms that both metaheuristic strategies contribute to reducing jitter over time, ensuring better QoS stability during handovers.

4.3 End-to-end Delay

End-to-end delay is the total time it takes for a video packet to travel from the sender to the receiver. It includes all sources of latency along the path, such as video encoding/decoding, packetization, buffering, transmission, and network routing delays. In video streaming and real-time communication, keeping end-to-end delay low is essential for smooth playback and natural interaction, because high delay can cause lag, stalls, and noticeable interruptions especially during mobility and handover situations.

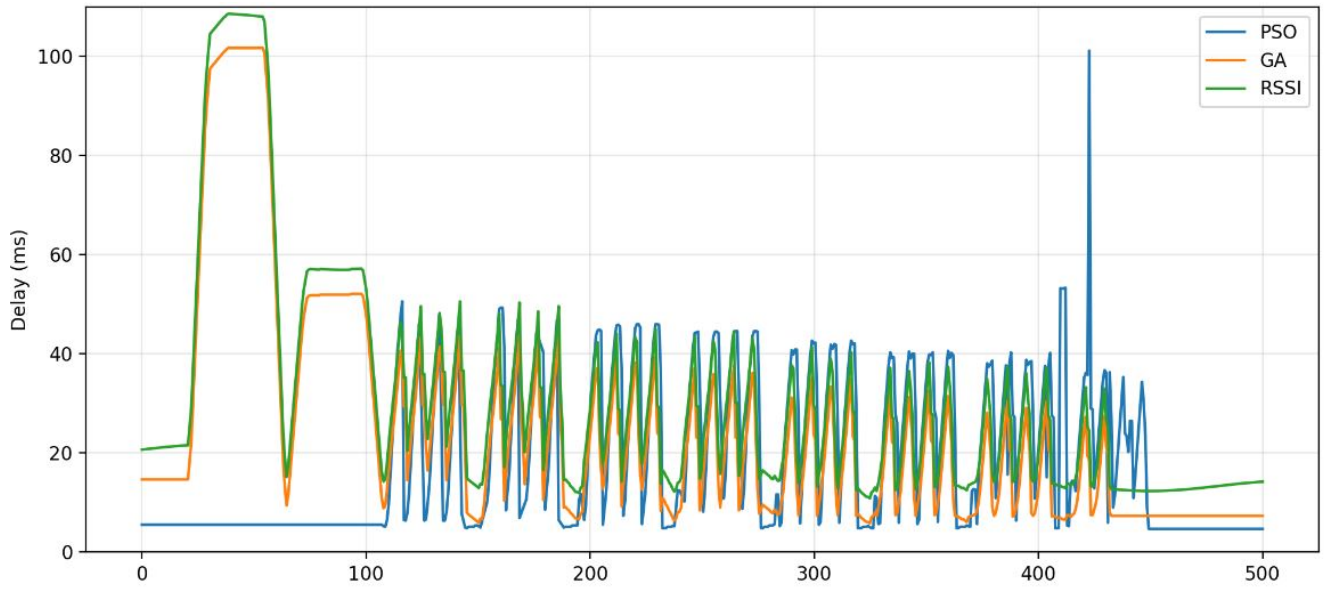


Figure 9. Comparison of average end-to-end delay over time.

Figure 9 illustrates the evolution of the end-to-end delay (ms) over simulation time for three handover strategies: PSO, GA, and the conventional RSSI-based method. End-to-end delay represents the total time required for video packets to travel from the sender to the receiver, including processing, transmission, routing, and handover-related interruptions. Lower delay values

indicate a more stable network and improved Quality of Service (QoS), especially for real-time video streaming applications.

At the beginning of the simulation (0–50 s), the three approaches exhibit relatively low delay values. However, a sudden increase appears around 50–70 s, where the delay sharply rises and reaches high peaks (above 100 ms), indicating a critical phase of mobility where handover events cause transmission instability. During this period, the RSSI-based approach shows the highest delay values, reflecting less efficient handover decisions under dynamic conditions.

After this transient phase, the delay decreases significantly and becomes more periodic, with oscillations occurring between approximately 100 s and 400 s, corresponding to repeated handover operations and network switching. In this interval, PSO consistently maintains lower delay levels compared to GA and RSSI, demonstrating better handover optimization and more stable packet delivery. The RSSI method remains less stable, with higher delay values and slower convergence.

Overall, the results confirm that the PSO-based approach provides the best delay performance, reducing end-to-end delay and improving transmission continuity for video streaming services, particularly under mobility and frequent handover scenarios.

4.4 Throughput

In video streaming communication applications, throughput is the amount of video and audio data that can be successfully sent over the network each second. It directly affects how smooth and clear the video looks: higher throughput usually means better video quality, less buffering, and fewer drops in resolution. If throughput becomes too low because of weak internet, congestion, or packet loss, the application may lower the video quality, freeze, or delay the audio to keep the call running.

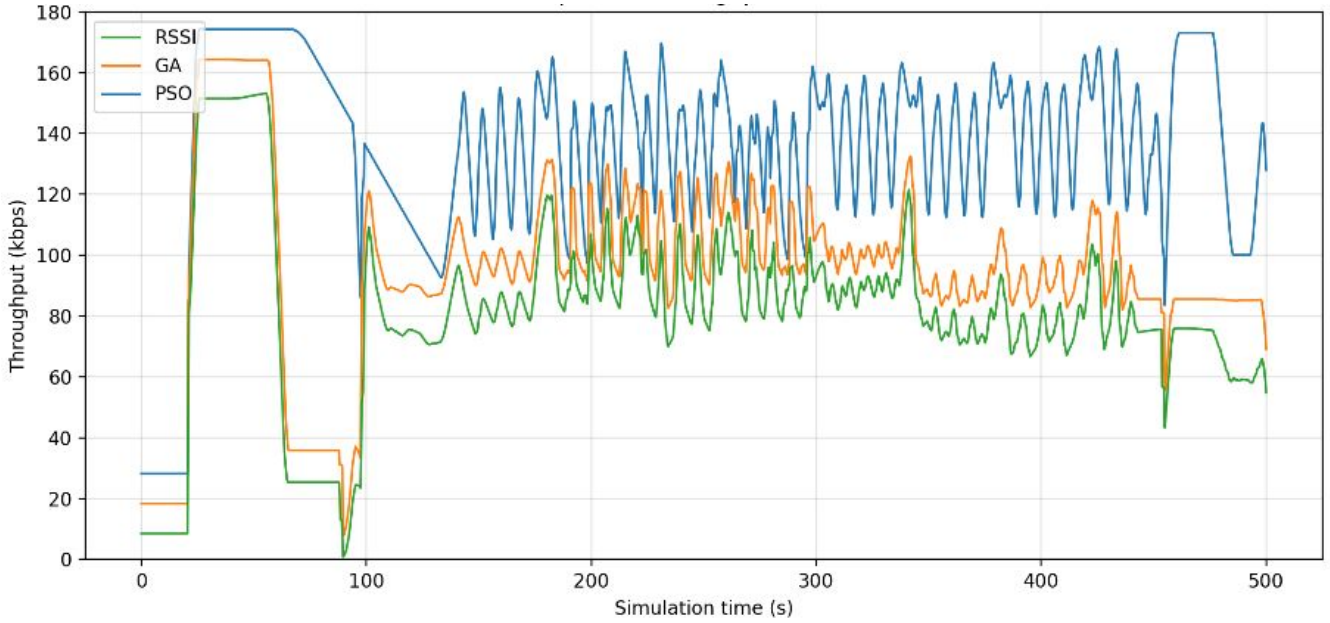


Figure 10. Comparison of average throughput over time.

Figure 10 shows the throughput evolution (kbps) versus simulation time (0–500 s) for three handover strategies: RSSI-based selection, GA, and PSO. Throughput reflects the effective data rate delivered to the user, and higher values indicate better QoS for video streaming.

At the start of the simulation, the curves exhibit an initial transient phase where throughput increases rapidly as the connection is established. Shortly after, a noticeable throughput drop appears (around the first handover interval), which is caused by mobility and the handover process. After this transition, the system enters a longer dynamic period where the throughput oscillates due to repeated handovers and varying radio conditions.

Across most of the simulation, the PSO-based approach achieves the highest throughput, remaining consistently above the other techniques and reaching peaks close to 170–175 kbps, which indicates a more efficient handover decision and better resource utilization. The GA-based strategy provides intermediate performance, generally maintaining throughput around 90–130 kbps, but with frequent fluctuations during mobility. In contrast, the RSSI-based method shows the lowest throughput values and higher instability, typically ranging between 70–110 kbps, highlighting the limitation of relying only on signal strength in heterogeneous environments.

Overall, the comparison confirms that PSO outperforms GA and RSSI in terms of throughput, providing a higher average

data rate and better stability over time. This improvement directly supports better QoS and contributes to a smoother QoE for real-time video streaming under mobility and frequent handover conditions.

4.5 Energy consumption

Energy consumption refers to the amount of energy spent by a mobile host when it switches its connection between different cellular (or heterogeneous) access networks. This consumption mainly comes from continuous radio measurements and scanning, signaling exchanges with network entities, authentication and re-association procedures, and the temporary use of additional processing to maintain service continuity (often involving retransmissions or duplicated control messages). In mobility scenarios, these operations can significantly increase battery consumption, so minimizing handover-related energy consumption is an important objective for improving device lifetime while preserving QoS/QoE for real-time applications such as video streaming.

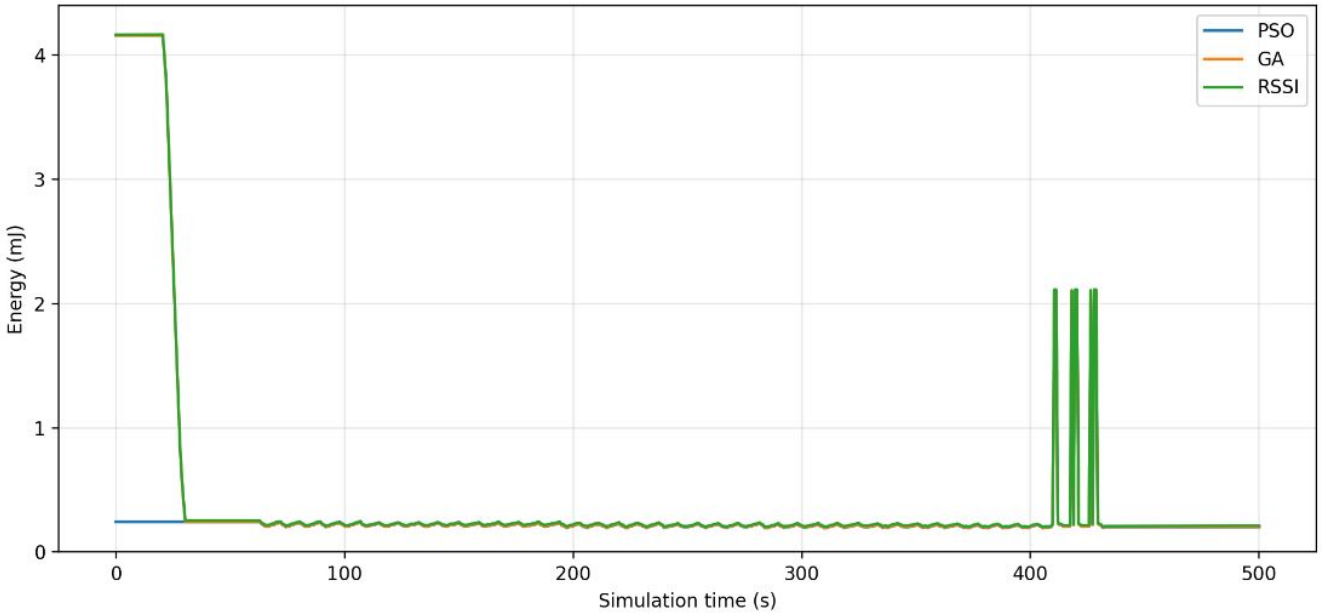


Figure 11. Comparison of average energy consumption over time.

Figure 11 reports the energy consumption (mJ) over the simulation time (0–500 s) for PSO, GA, and the conventional RSSI-based handover strategy. At the beginning of the simulation, there is a high energy peak (≈ 4 mJ) for the RSSI-based approach (and it may overlap with GA at the very start), which corresponds to the initial connection procedures and intensive radio activity (scanning/association and signaling). After this initialization phase, the energy consumption drops quickly and all methods operate at a low steady level (around a few tenths of mJ), showing that the system becomes stable during normal transmission. A clear difference appears later in the simulation: the RSSI method exhibits several sharp energy spikes around 400–430 s, reaching about 2 mJ. These indicate additional overhead caused by unnecessary or poorly-timed handovers. In contrast, PSO and GA remain nearly flat and stable without large peaks, meaning they reduce handover related overhead and avoid energy expensive switching events.

The results confirm that metaheuristic based handover optimization (especially PSO) attains more energy efficient mobility management than the RSSI baseline, which is important for extending battery lifetime while maintaining QoS for real-time services such as video streaming.

4.6 Results comparison

Overall, the simulation results demonstrate that metaheuristic-based handover optimization improves both QoS and energy efficiency compared to the conventional RSSI-based approach. Across all metrics, RSSI selection is the least stable under mobility because it relies only on signal strength, which can trigger unnecessary handovers. GA provides intermediate performance by improving decision quality, but it still exhibits higher variability in several intervals. PSO consistently achieves the best global performance by selecting more suitable attachment points, leading to lower packet loss, jitter, and delay, while maintaining higher throughput and avoiding energy-expensive handover events. These improvements directly support better QoE for video streaming (higher MOS/PSNR predictions). Table 7 summarizes and compares the performance of the

three handover strategies (PSO, GA, and RSSI-based selection) in terms of the main QoS metrics and energy consumption, highlighting the general trend observed in the simulation results.

Table 7. Summary comparison of PSO, GA, and RSSI-based handover strategies.

Metric	PSO (Metaheuristic)	GA (Metaheuristic)	RSSI (Baseline)	Main observation from figures
Packet loss (%)	Lowest, more stable	Medium, oscillatory	Highest	PSO minimizes losses under mobility; RSSI suffers most during handover
Jitter (ms)	Lower / stable after transient	Close to PSO, slightly higher in some intervals	Higher, more variable	Metaheuristics reduce jitter after adaptation (≈ 200–500 s)
End-to-end delay (ms)	Lowest average, fewer peaks	Medium	Highest peaks, less stable	RSSI shows larger delay spikes around strong mobility/handover periods
Throughput (kbps)	Highest, best continuity	Medium	Lowest	PSO sustains higher throughput and better stability over 0–500 s
Energy (mJ)	Lowest / flat (stable)	Low / stable	Highest, spikes	RSSI shows noticeable energy spikes (≈ 400–430 s) from extra handovers

4.7 Best fitness

The plot in Figure 12 compares PSO and GA best fitness across 50 iterations. PSO begins at about 135 and gradually decreases until it reaches about 25 at the final iteration. GA begins at about 140 and decreases over time, ending at about 32. Around iteration 10, PSO is close to 85 while GA is close to 95; around iteration 20, PSO is about 53 while GA is about 63; and around iteration 30, PSO is about 37 while GA is about 47. Overall, PSO stays lower than GA for most of the iterations and finishes with the best (lowest) final fitness.

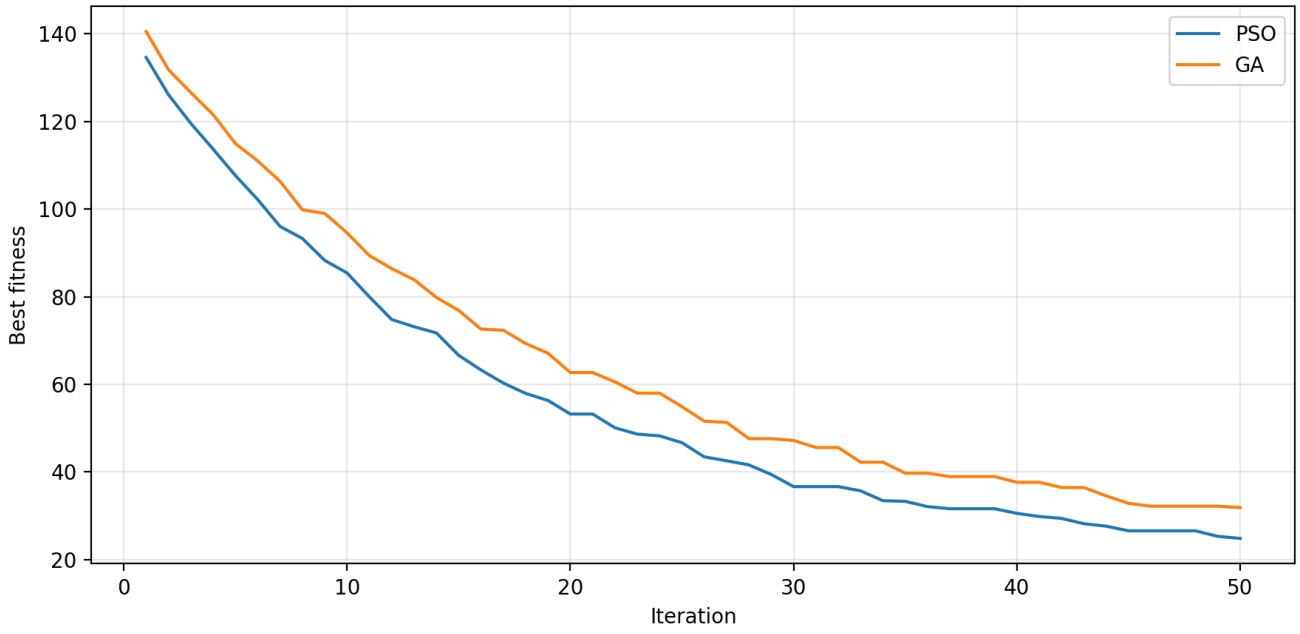


Figure 12. Best fitness comparison.

5 Conclusion

This paper addressed the problem of maintaining acceptable video Quality of Experience (QoE) during mobility in heterogeneous LTE/Wi-Fi environments interconnected through a secure MPLS core. To tackle the combined challenges of vertical handover and QoS degradation, we proposed an integrated framework that couples network-layer mobility based on MIPv6 with an

SDN-controlled, QoE-driven handover decision mechanism. A lightweight MLP model predicts MOS and PSNR from real-time QoS indicators (throughput, delay, jitter, and packet loss) and UE energy consumption, and these predictions are then used to trigger metaheuristic optimization modules based on GA and PSO for access point selection in the HetNet. In this context, we introduced a new notion of fitness score, which jointly combines QoE and QoS indicators into a single metric that drives the optimization process toward handover decisions that preserve user-perceived quality. Simulation results obtained in OMNeT++/INET demonstrate that combining QoE prediction with the proposed fitness-based, metaheuristic-driven handover mechanism significantly improves the stability and efficiency of mobility management compared with a conventional RSSI-based strategy. Across all evaluated metrics the RSSI-based approach exhibits the weakest performance and the highest variability under mobility. GA provides intermediate performance, improving decision quality but still showing noticeable fluctuations. PSO consistently achieves the best overall behavior, lower loss, jitter, and delay, higher throughput, and reduced energy during handover phases. These gains translate directly into better predicted MOS/PSNR values and smoother video streaming continuity during vertical handovers. The proposed QoE aware, fitness guided, metaheuristic assisted handover framework shows that integrating learning-based QoE prediction with SDN and intelligent optimization over a secure MPLS backbone is a promising direction for next-generation HetNets. By jointly considering QoE and QoS within the fitness score, the system moves beyond traditional metric-by-metric handover policies to provides a more holistic and user centric mobility management solution for real-time video services.

In future work, the proposed QoE-aware handover framework can be extended and validated in several directions. First, the current LTE/Wi-Fi scenario could be generalized to denser, multi-cell 5G/6G HetNets with more access technologies and a larger number of mobile users, in order to assess scalability and robustness under heavy load and interference. Second, the offline MLP-based MOS/PSNR predictor could be replaced or complemented by an online/continual learning model that adapts its parameters to changing traffic patterns, codecs, and mobility profiles, thus maintaining accurate QoE estimation over time. Another promising direction is to move from a single-objective optimization (mainly focused on QoE) to a truly multi-objective formulation that jointly optimizes QoE, energy consumption, and possibly security constraints, with dynamic weighting depending on the user's battery level, application type, or operator policy.

Conflict of Interest

The authors declare that they have no conflict of interest.

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Author Contributions

Narimane Elhilali: Writing – original draft, Software, Resources, Project administration, Methodology, Investigation, Data curation, Conceptualization. Mostapha Badri, Mouncef Filali Bouami: Writing – review & editing, Supervision, Project administration, Conceptualization.

Data Availability

The data supporting the findings of this study are available from the authors upon reasonable request.

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