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Content-aware and QoE Optimization of Video Stream Scheduling over LTE Networks using Genetic Algorithm and Random Neural Networks

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Abstract

Long Term Evolution (LTE) networks support Quality of Service (QoS) of multimedia services with fast communication connectivity, high data transfer speed and high level of security. Video streaming over LTE networks is one of the highest proportions of global mobile data traffic and is growing; this has led to the development of several scheduling algorithms aimed at improving the performance of these networks. The performance analysis and evaluation of existing scheduling algorithms are generally limited to QoS parameters. It is not clear how these scheduling algorithms perform in terms of Quality of Experience (QoE) which is the overall acceptability of a service or application, as perceived subjectively by end users. Video content has a major impact on QoE; thus its analysis in scheduling algorithms performance is critical. The aim of this study is to classify video content based on the impact of video content on quality over LTE networks. This classification is then used to develop novel QoE-aware optimization scheduling of video traffic in order to achieve maximum QoE. Our approach focuses on the development of optimization downlink scheduling based on a novel integration between random neural networks (RNN) and genetic algorithms (GA) to learn complex non-linear mapping of QoE and to search for the optimal parameters, respectively. An open source simulation tool for LTE networks (LTE-Sim) has been used to collect unique RNN training database based on existing scheduling algorithms. A comparison between the proposed scheduler and state-of-the-art LTE downlink scheduling algorithms (FLS, EXP-rule, and LOG-rule) has been made under different network conditions. Simulation results showed an increase in performance of about 15% in terms of QoE and throughput while maintaining fairness.

Keywords: *Content Classification, GA, RNN, QoE, Scheduling Algorithm*

1. Introduction

Streaming video content over mobile communications has become a major contributor to the Internet data traffic over the World Wide Web (WWW). A recent study conducted by Cisco [1] indicates that mobile video will grow at a compound annual growth rate (CAGR) of 62% between 2015 and 2020, higher than the overall average mobile traffic CAGR of 53% as shown in Fig. 1. Mobile video traffic represented more than 50% of global mobile data traffic beginning in 2012, and more than 70% of the mobile data traffic will be video by 2020, indicating that it is already affecting traffic today, not just in the future. With the growing demand for video-based applications, granting the QoS to users has become a big challenge. To overcome all these challenges, the 3rd Generation Partnership Project (3GPP) group has proposed a new generation of wireless communication known as LTE. Based on advanced technologies, the LTE system could provide a significant enhancement to user experience and system performance. Due to the shortage of radio resources, the optimal use of the available resources is significant for scheduling algorithms to improve users' QoS. Classical scheduling algorithms such as Proportional Fair (PF), Frame Level Scheduler (FLS), and Modified Largest Weighted Delay First (M-LWDF) are fundamentally channel-aware and aim to maximize the network

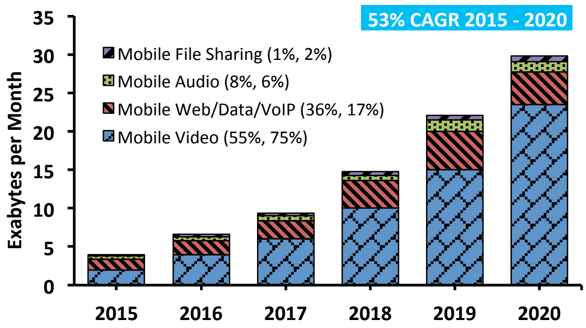

Fig. 1. Forecast of global mobile data traffic growth

throughput and/or maintaining a degree of fairness among users. However, channel-ware algorithms could not achieve the best possible quality for real-time video streaming over wireless networks. The architecture of wireless systems, in fact, operates with the Open Systems Interconnect (OSI) layered design, in which each layer does not consider the constraints of other layers. This is not appropriate for the increasing demand of real-time applications, especially video applications which are highly sensitive to the packet loss and transmission rate. Therefore, higher QoE performance could be

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obtained if the service provider could regularly measure the video quality and resource utilization efficiency by taking constraints of different layers into consideration. Several system parameters have different impacts on users' QoS which could fundamentally be classified as an application or network parameters. According to the study conducted by Telecoms communication in 2015 [2], most of the network operators see video content streaming as one of the highest profitable LTE services. The Telecoms Intelligence Annual Industry Survey indicates that about 75% of respondents identified video content as one of the highest services enabled by LTE and the most revenue generating potential. Consequently, we take the video content type and level of users' satisfaction of quality into account to design optimization scheduling algorithm of the video stream in order to provide high-quality video transmission over LTE networks.

In general, the most important goal of an optimization of video streaming is to improve QoE. This is associated with the network ability to choose optimal parameters and the appropriate scheduling matrix to achieve the best QoS and to increase network utilization. The main contributions of this paper are:

(i) An extensive QoE database has been developed based on different content types (CT) of video clips using LTE-Sim [3], under different network conditions. The obtained database is utilized in a unique classification of the video contents based on their impact on QoE.

(ii) The QoE database is also used to train the QoE prediction model using RNN techniques. A novel four layers feed-forward RNN model is presented that learns complex non-linear mapping of QoE. The distinctive internal structure of this model gives it greater accuracy and performance than previous models reported in the literature.

(iii) A unique interaction between RNN and GA has been developed to explore the optimal strategy profile for network users based on QoE prediction values. The developed RNN-GA framework has been used to optimize the distribution of available network resources in correspondence with the type of video content in order to maximize QoE while guaranteeing fairness among users.

The rest of the paper is organized as follows. Section 2 presents an overview of LTE system and QoS-aware downlink scheduling algorithms. Section 3 presents the fundamentals of RNN, GA, and QoE database collection. Section 4 discusses the impact of quality parameters on video quality, classifies the video content and finds the degree of influence of quality parameters. Section 5 presents QoE-aware optimization proposed model. Section 6 presents and discusses results. Section 7 concludes the paper and outlines the future work.

2. Overview on LTE Networks

LTE stands for "Long Term Evolution" and was first proposed in Toronto 2004 by the third generation partnership project (3GPP) as the preliminary version of the 4G wireless communication systems. The purpose of LTE is to provide higher radio access data rate, low latency, and high security to achieve great capacity and reliable high speed in mobile communication networks. Besides, LTE technology guarantees enhanced spectrum flexibility and compatibility with other 3GPP radio access technologies. In addition, Orthogonal Frequency Division Multiplexing Access (OFDMA) is applied in downlink side to provide higher capacity and eliminate the intra-cell interference with sturdiness to the fading nature of wireless channel in the time-frequency domain, OFDMA technology has been selected instead of CDMA in 3G as the radio access technology which offers greater network capacity. On the other side, SC-FDMA (Single Carrier-Frequency Division Multiple Access) is applied in uplink aims to reduce the user's energy consumption [4]. LTE networks characterized by a high degree of flexibility, both time division duplex (TDD) and frequency division duplex (FDD) multiple access techniques have been supported. Moreover, the overall LTE network architecture, which is known as system architecture evolution (SAE), has been improved using a new antenna technology so-called multiple in multiple out (MIMO) and employ it with OFDM to provide data rate up to 100 Mb/s download and 50 Mb/s upload. LTE network supports a wide range of channel bandwidth from 1.4 up to 20 MHz; this makes it highly flexible and scalable to develop in different environments. These significant advantages of LTE networks granted faster speed about 10 times than 3G networks, LTE networks are often up to 10 times faster than 3G networks with speeds commonly between 20Mbps and 30Mbps. The quality of service (QoS) support is one of the most important features of LTE networks [5]. Although the existence of many protocols supports the QoS, applying it in live LTE networks remains challenging due to several factors, including the channel characteristics, changing send bit rates, handoff support among a variety of networks, bandwidth allocation propagation conditions and application types [6].

2.1. Scheduling Algorithms in LTE Networks

Packet scheduling algorithm which is also known as dynamic resource allocation is a significant feature of mobile communication systems since it is responsible for the distribution of available network resources among users to meet the QoS according to individual requirements. The main function of the scheduling algorithms is to maximize the performance of LTE networks while maintaining fairness among network users. Broadcast of the data over LTE networks is organized by entities of frequency and time domain as physical resources. The Frequency Domain Packet Scheduling (FDPS) allocates Resource Blocks (RBs) to each user and Time Domain Packet Scheduling (TDPS) selects a subset of active users in current Transmission Time Interval (TTI). RB is the smallest allocation unit of resource scheduling that is a combination of one sub-frame in time over 12 consecutive sub-channels with the length of 180 KHz. Each sub-frame divides into two-time slots of 7 OFDM symbols which represent one TTI continue for one millisecond (ms) [7]. Fig. 2 shows the physical LTE radio resources in the time-frequency domain. In details, the scheduling strategy repeats every TTI and can be divided into several steps as follows: (i) each user explores the quality of the signal and sends feedback of Channel Quality Indicator (CQI) of the signal status to the enhanced NodeB (eNB). (ii) The eNB uses the information obtained by CQI for the allocation Resource decisions and fills up an RB. (iii) The best MCS selected by AMC to use by scheduled users for data transmission. (iv) The allocated RBs and the selected MCS with all users' information send to the UEs on the PDCCH. (v) Each UE reads the PDCCH payload and accesses to the proper PDSCH payload [4].

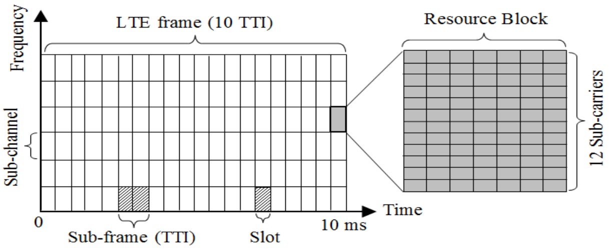

Fig. 2. Time-Frequency LTE radio resources grid

In general, scheduling algorithms classify into three strategies as follows: (i) Channel insensitive Strategy, (ii) Channel sensitive and QoS-unaware Strategy, and (iii) Channel sensitive and QoS-aware Strategy. Since one of the main features of LTE system is QoS, our focus will be on the strategy of channel sensitive and QoS-aware. Table 1 summarizes the most important QoS-aware scheduling algorithm in terms of target, key aspects, and input parameters.

Table 1. Scheduling algorithms based on QoS

Name	Target	Key Aspects	Parameters
PF [8]	Fairness & bitrate	Balancing between requirements of spectral efficiency and fairness.	SINR & Throughput.
PSS/PF_{sch} [9]	Fairness & bitrate	Joint TDPS and FDPS structure, PSS at TDPS and PF_{sch} at FDPS.	SINR & Throughput.
M-LWDF [10]	Delay-Bounded	PF for channel awareness and LWDF scheduler for the bounded delay.	SINR, D_{HOL}, Delay, PLR & Throughput.
EXP/PF [10]	Delay-Bounded	Exponential rule for the bounded delay and PF for channel awareness.	SINR, D_{HOL}, Delay, PLR & Throughput.
LOG rule [11]	Delay-Bounded	Logarithm rule for the bounded delay and PF for channel awareness.	SINR, D_{HOL}, Max Delay & Throughput.
EXP rule [11]	Delay-Bounded	Exponential rule for the bounded delay and PF for channel awareness.	SINR, D_{HOL}, Max Delay & Throughput.
FLS [12]	Delay-Bounded	Double layer scheduler structure and Control law for RB preemption of real-time flows.	Max PLR & Queue Length.
DPS [13]	Delay-Bounded	Prioritization of delay constrained flows. RBs upon meeting QoS needs are allocated to the user with the highest priority.	SINR, D_{HOL}, Max Delay & Throughput.
MQAF [14]	Bit rate	Clustering GBR and non-GBR by allocating RB to GBR users to meet its needs and leave spare RB to non-GBR.	SINR & Throughput.
QoSP [15]	Bit rate	Priority: RBs upon meeting GBR needs are allocated beginning with the users have the highest priority	SINR, D_{HOL} & Throughput.
CGTVTM [16]	Delay-Bounded & bitrate	Exponential rule for the bounded delay and virtual token mechanism for minimum guaranteed bitrate.	SINR, D_{HOL}& Max Delay.
QoE-aware [17]	Maximum QoE	Consider a resource allocation scheme aimed to maximize the overall of Mean Opinion Score (MOS) [18].	MOS, Min & Max Delay.
QoE-based [19]	Minimum change of the QoE	Consider a resource allocation scheme aims to minimize the temporal change of the video quality with higher QoE.	CQI, BLER & MOS.
QoE-Oriented [20]	Maximum QoE	Consider a resource allocation scheme aimed at maximizing the QoE for RT and nRT traffic.	Max PLR, D_{HOL}, CQI & MOS.
QoE-based [21]	Maximum QoE	Exploring the optimal strategy profile for users aimed to max QoE while guaranteeing fairness	SBR, MCS, Playback Time & MOS.
QoE-aware [22]	Maximum QoE	Optimizing the distribution of available resources aimed at max QoE and maintaining fairness.	MOS, SBR, SM & Max Delay

Recently video transmit over LTE networks is one of the highest percentages of mobile traffic and its applications have been growing rapidly. Therefore, the objectives of scheduling strategies are shifted from improving QoS to improving QoE. Taboada *et al.* in [17] proposed a novel download scheduling algorithm based on minimum delay aimed to maximize QoE. However, they do not consider any of application layer parameters. In [19] and [20] two resource allocation schemes were presented aimed to maximize QoE however, both had only applied to the wireless network. Ying *et al.* in [21] proposed a cross-layer design scheme for optimizing resource allocation of video applications over LTE networks based on QoE. However, the proposed scheme had only considered the influence of SBR on the application layer. Our previous work in [22] addressed some of these challenges and presented the QoE-aware optimization of video stream downlink scheduling over LTE networks using RNN and GA in terms of learning complex non-linear mapping and searching for the global optimum through particular parametric space, respectively. To the best of our knowledge, content-aware and QoE optimization of video stream scheduling over LTE networks have not yet been considered in the recent literature. Our work bridges this gap by proposing a preliminary study on this very interesting and challenging problem.

2.2. General Scheduling Metrics in LTE System

The key function of LTE scheduling algorithms is the optimum distributing of available resources among active network users. Table 2 shows the most common scheduling algorithms used for allocating network resources in LTE system. Network resources are allocated to each user based on the comparison of Resource Block (RB) metrics: the k^{th} RB is allocated to the j^{th} user if its metric $m_{j,k}$ is the highest one accordingly, this user will serve first. The value of scheduling metric determines according to the priority and performance requirement based on the following factors [23]:

- Quality of Service (QoS), according to QoS requirements, the lowest Quality Class Identifier (QCI) value has the highest metric.
- Channel Quality, according to the feedback of Channel Quality Indicator (CQI) value, the highest expected throughput has the highest metric.
- Status of transmission queues, according to the status of queues, the longest queue has the highest metric.
- Resource Allocation History, according to the past achieved performance, the lowest past throughput has the highest metric.
- Buffer State, according to the buffer condition at the receiver side, the highest available space in the buffer has the highest metric.

Table 2. LTE Scheduling algorithms

Algorithm	Scheduling Matrix (SM)	Expression Meaning
1. PF	$m_{i,k}^{PF} = d_k^i(t)/\overline{R^i}(t-1)$ $d_k^i(t) = \log[1 + SINR_k^i(t)]$	$m_{i,k}$: Generic metric $d_k^i(t)$:Expected data rate
2. M-LWDF	$m_{i,k}^{M-LWDF} = -\dfrac{\log \delta_i}{\tau_i} . D_{HOL,i} . m_{i,k}^{PF}$	D_{HOL}: Head of line packet delay
3. FLS	$m_{i,k}^{PF\ con\_flow} = d_k^i(t)/\overline{R^i}(t-1)$	$R^i(t)$: Average throughput
4. EXP/PF	$m_{i,k}^{EXP/PF} = exp\left(\dfrac{\alpha_i . D_{HOL,i} - x}{1+\sqrt{x}}\right) . m_{i,k}^{PF}$	$x = \dfrac{1}{N_{rt}} \sum_{i=1}^{N_{rt}} \alpha_i . D_{HOL,i}$
5. EXP rule	$m_{i,k}^{EXPrule} = b_i exp\left(\dfrac{\alpha_i . D_{HOL,i}}{c+\sqrt{x}}\right) . \Gamma_k^i$	τ_i: Delay Threshold for the i^{th} user
6. LOG rule	$m_{i,k}^{LOGrule}$ $= b_i \log(c + a_i D_{HOL,i}) . \Gamma_k^i$	Γ_k^i: Spectral efficiency

2.3. Scheduler Algorithms Parameters

Several parameters have been used to calculate the scheduling matrix values, which is then used to prioritize network resources allocation to active users. The most important of these parameters can be summarized below:

- Throughput is the rate of successful data delivery over a wireless communication channel.
- The signal to interference plus noise ratio (SINR) is a measurement of channel quality over wireless communication for link adaptation along with packet scheduling.
- Perceived quality of the end user (QoE) is a measure of the overall acceptability of a service or application as perceived by the customer.
- Target delay is the maximum time allowed for the packets to remain in the queue before it is sent or dropped.
- Head of line delay is the time delay of the first packet to be transmitted.
- Queue length is the length of data traffic in the queue before scheduling.

3. Overview of RNN and Genetic Algorithm

This section provides a more detailed description of the system and the intelligent learning models as follows: (3.1) Summary of Random Neural Networks, (3.2) Summary of Genetic Algorithms and (3.3) QoE Database Collection.

3.1. Random Neural Networks

Random neural networks (RNNs), is a machine learning technique, using interconnected processing elements known as neurons, aim to process the information by their state response and learn via previous examples and training. The key purpose of the RNN models is to learn the input-output relationship, transform the inputs into meaningful outputs, and provide effective solutions to unseen problems. RNNs were first introduced in 1989 by Gelenbe [24]. RNNs are mathematical models that combine features of both the classical artificial neural networks (ANNs) and of queuing models but cope with the limitations of ANNs and have advantages. These models have several features that make them more appropriate for modeling the QoE of multimedia traffic. Researchers have been inspired to form the ANNs in order to mimic these large amounts of interconnections observed in the human brain. RNN has been efficiently applied in various applications as learning tools and has shown high accuracy. The internal structure of RNN models can describe as a set of interconnected neurons as shown in

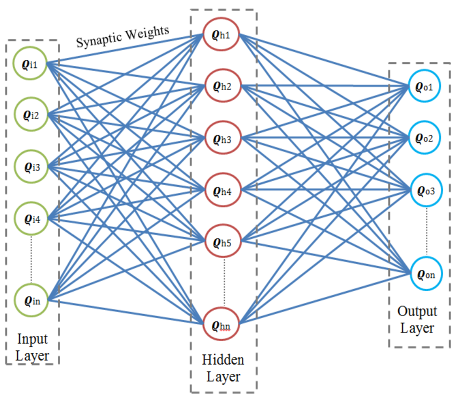

Fig. 3.

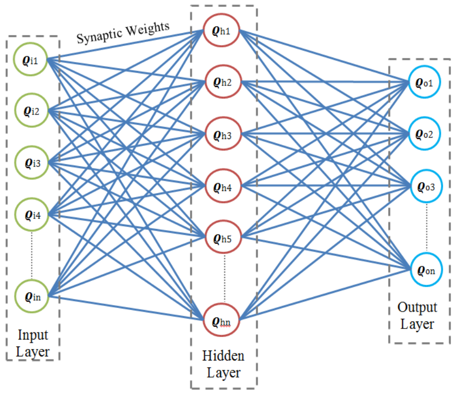

Fig. 3. Neural network model

The neurons exchange signals with each other and also with the environment. The signals are transmitted directly between neurons from layer to layer, or between neurons and the environment. Each neuron is represented by a positive or negative integer one '+1' or '-1', whose value increases by one when it receives excitation spikes and decreases by one when an inhibition spike arrives. Thus, the excitation spikes are represented as '+1' and inhibition spikes are represented as '-1'. The spikes can originate either from outside the network or from another neuron within the network. Neurons whose excitation state is positive are allowed to send out spikes to either kind of neuron in the network. When a neuron sends out a spike, it loses one unit of potential, going from the state (q_i) to ($q_i - 1$). The probability that the spike signal sent out by neuron i to neuron j is a positive one is represented as ($p^+_{i,j}$), and the probability that it is a negative one is represented as ($p^-_{i,j}$); the signal that leaves the network to travel to the environment is represented by d_i, where N is the number of neurons for all i=1,…, N.

$$d_i + \sum_{j=1}^{N} (p^+_{i,j} + p^-_{i,j}) = 1 \qquad (1)$$

When a neuron receives a positive signal, either from another neuron or from the environment, its potential is increased by 1; conversely, if it receives a negative signal, its potential decreases by 1 if it was strictly positive, and it does not change if its value was 0. Similarly, when a neuron sends a signal, positive or negative, its potential decreases by 1; it was necessarily strictly positive since only excited neurons send signals. Neuron i receives signals from outside according to a Poisson process with rate (λ^+_i) for a positive signal and (λ^-_i) for a negative one. When neurons are excited they are denoted as ($w^+_{j,i}=r_j p^+_{j,i}$) and ($w^-_{j,i}=r_j p^-_{j,i}$); the w represents weight. These weights w may be interpreted and represent the excitatory and inhibitory spike rates, and they are typical interconnections weights of a neural network that RNN learns through the process of training. The non-linear system of equations (2), (3) and (4) allows computing the ϱ of the input layer (ϱ_i), hidden layer (ϱ_h) and of output layer (ϱ_o) neurons directly from the values for input layer ones [25].

$$\varrho_i = \frac{\lambda^+_i}{r_i + \lambda^-_i} \qquad (2)$$

$$\varrho_h = \frac{\sum_i \varrho_i \omega^+_{i,h}}{r_h + \sum_i \varrho_i \omega^-_{i,h}} \qquad (3)$$

$$\varrho_o = \frac{\sum_h \varrho_h \omega^+_{h,o}}{r_o + \sum_h \varrho_h \omega^-_{h,o}} \qquad (4)$$

3.2. Summary of Genetic Algorithms

A Genetic Algorithm (GA) is a search technique based on the concept of evolution and the survival of the fittest [26]. GA is inspired by Darwin's theory of eclecticism where passed optimum benefits through successive breeding operations and the strengthening of these qualities. In general, the working mechanism of GA can be summarized in the following steps: (*i*) a population is created with a group of individuals selected randomly. (*ii*) The individuals in the population are then evaluated based on how well they perform at the given task (fitness function). (*iii*) Two individuals are then selected according to their fitness value; the higher fitness has, the higher chance of being selected. (*iv*) The individuals then reproduce to create one or two offspring, after which the offspring are mutated randomly. This continues until a suitable solution has been found or a certain number of generations have passed, depending on the needs [27]. GA has been used to solve both optimization problems that strike a remarkable balance between exploration and exploitation of search space based on a natural selection process that mimics biological evolution.

3.3. QoE Database Collection

The most effective parameters of video quality related to video applications in LTE networks need to be identified and chosen. Ten video clips; (Akiyo, Carphone, Coastguard, Football, Foreman, News, Stefan, Suzie, Tempete, and Tennis) that available in Video Trace Library [28], were used for the model comparison. The video clips were selected from various classes, according to the spatial-temporal activity. Each clip was coded in H.264 in four send bitrates (128 kb/s, 242 kb/s, 440 kb/s and 880 kb/s), in three frame rates (10 fps, 20 fps, and 30 fps) and in two display sizes (QCIF and CIF). Transmission impairment was performed with the percentage of packet loss between 0% and 2%. The simulation scenario shown in Fig. 4 was used to create a degraded video database composed of sequences corresponding to different configurations of the selected parameters. LTE-Sim that developed by G. Piro *et al.* [3] was used to generate a video distortion database as follows: a realistic multi-cell scenario was made which had a radius of 500 meters, and the 19 cells, each cell has one eNB and number of 10 to 30 users (UEs). The UEs' movement traveling cells with one video flow were simulated with the random walk mobility model with a speed of 3 to 120 km/h. There are three sender nodes, one video source, one VoIP source and one best-effort source, as shown in Fig. 4. A trace-based application was used as video traffic, which delivers packets that are based on the realistic video trace files. The simulation parameters are summarized in Table 3. Five simulations were run for each number of users with six different scheduling algorithms shown in Table 2 to calculate the average of MOS, throughput, and fairness.

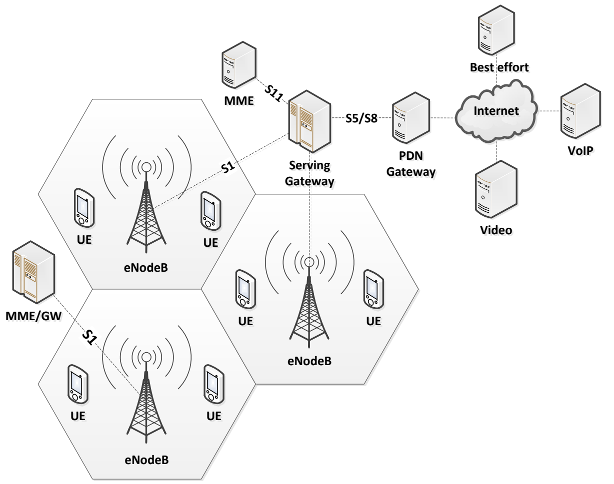

Fig. 4. LTE network topology

In each case when the transmission of video takes place from the source to the destination, every configuration with its defined input data must be mapped into the system composed of the source, the receiver, and LTE network. The destination will store the corresponding values of the parameters of the transmitted video sequence. Then, by running the simulation several times, we generated and stored a set of distorted video clips with corresponding parameters.

Table 3. Simulation parameters

Parameter	Value
Simulation time	100 s
Number of cells	19 eNodeB
Physical details	Carrier frequency: 2 GHz; Downlink bandwidth: 5 MHz; Modulation scheme: QPSK, 16QAM, and 64QAM; eNodeB: Power trans = 43 dBm;
Cell layout	Radius: 0.5 KM
Number of users	10, 15, 20, 25, 30
User speed	3, 30, and 120 KM/H
Traffic model	Video traffic type: H.264, VoIP, and Best-effort

When the distorted database of the video traffic is ready, the open source framework 'Evalvid' [29] then used to compare the original and distorted video sequences. A PSNR metric which measures the quality by simple pixel-to-pixel comparisons was chosen as an objective quality assessment parameter; because it is the most commonly used and represents a high degree of correlation with perceived video quality of the end user [21]. Then a set of PSNR values were obtained by comparing the original (transmitted) and distorted (received) video sequences. The corresponding MOS values were extracted as shown in Table 4. The PSNR and MOS values with the corresponding parameters' values related to network, application, and LTE layers were stored in a second database called the QoE database.

Table 4. Possible PSNR to MOS conversion [29]

PSNR [dB]	MOS	Quality
> 37	5	Excellent
31 – 37	4	Good
25 - 31	3	Fair
20 – 25	2	Poor
< 20	1	Bad

4. The Relationship between the Objective Quality Assessments of Video and its Content

Based on the QoE database introduced above, the relationship between objective video quality and video contents were analysed. Firstly, the degree of impact of each quality parameter on video quality was found, then video content was classified on the basis of an objective video quality evaluation (PSNR/MOS scores), and finally, our classified contents were compared to the spatial and temporal dynamics classification.

4.1. Impact of Quality Parameters on Video Quality

In this section, the effect of video content type on video quality has been studied by analysis its impact with the selected quality parameters (SBR, FR, RES, and PLR). In order to have a clear and easy analysis, we selected a set of 3D figures in which we varied one parameter with all available content types and kept the other three fixed. The PSNR scores were computed as a function of the values of the parameters above.

- *Video Content vs. PSNR vs. Send Bitrate*

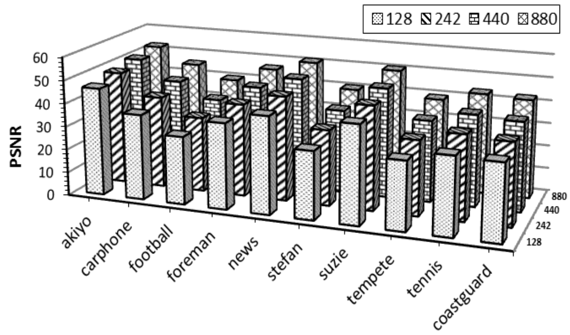

Fig. 5 shows the PSNR scores: the video quality increases when the send bitrate (SBR) increases from 128 kb/s up to 880 kb/s. We observed that with a higher SBR, the video quality was excellent (PSNR ≥ 50 dB in news videos); however, the quality fades (to PSNR < 27 dB) with decreased SBR, which was not an acceptable value to meet communication quality requirements.

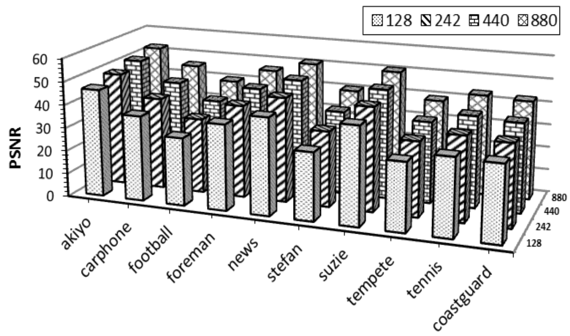

Fig. 5. Video Content vs. PSNR vs. SBR

- *Video Content vs. PSNR vs. Packet Loss Rate*

Fig. 6 shows the PSNR scores: the video quality decreases when the packet loss rate (PLR) increases from 0% up to 2%. We observed that with a lower PLR, the video quality was excellent (PSNR up to 49 dB); however, the quality fades rapidly (to PSNR < 25 dB) with increased PLR, which was not an acceptable value to meet communication quality requirements.

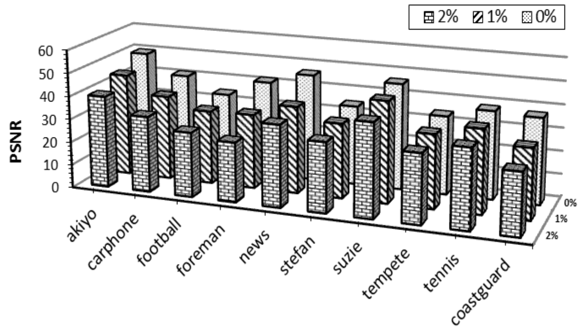

Fig. 6. Video Content vs. PSNR vs. PLR

- *Video Content vs. PSNR vs. Frame Rate*

Fig. 7 shows the PSNR scores: the video quality increases when the frame rate (FR) decreases from 30 f/s to 10 f/s. We observed that with a lower FR, the video quality was excellent (PSNR up to 50 dB); however, the quality fades (to PSNR up to 30 dB) with increased FR, which is an acceptable value to meet communication quality requirements.

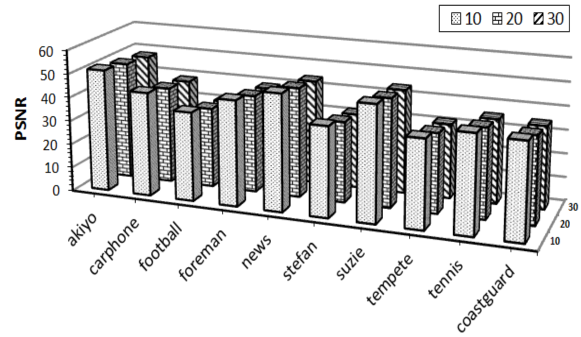

Fig. 7. Video Content vs. PSNR vs. FR

- *Video Content vs. PSNR vs. Resolution*

Fig. 8 shows the PSNR scores: the video quality decreases when the resolution (RES) increases from QCIF to CIF. We observed that with a lower revaluation, the video quality was excellent (PSNR up to 50 dB); however, the quality fades (to PSNR up to 30 dB) with increased RES, which is an acceptable value to meet communication quality requirements.

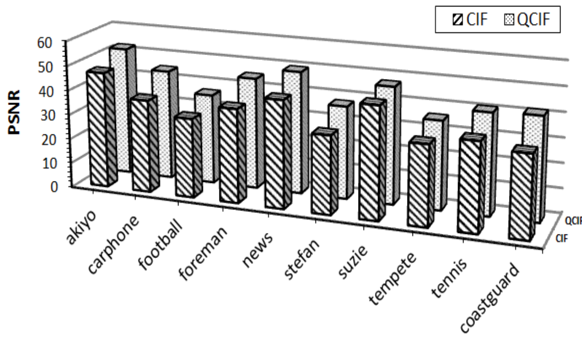

Fig. 8. Video Content vs. PSNR vs. RES

In conclusion, we can confirm that the SBR effect is substantial and comparable to that of PLR. When the SBR increases, the quality increases too, particularly in the case of poor conditions (i.e. lower values of SBR or higher values of PLR), while decreasing FR and RES improve video quality, especially in right conditions (high SBR and low PLR). Increasing the SBR improves the video quality with no packet loss. However, raising the SBR only improves the QoE if the link bandwidth (LBW) at a bitrate greater than or equal the SBR. If the LBW is less than the SBR, the video quality worsens due to network congestion issues.

4.2. Content Classification Model

Video contents were classified according to the PSNR scores obtained from the SBR, FR and RES parameters in the application layer, from PLR in the network layer and the scheduling algorithm in the LTE layer. Cluster analysis [30] is one of the most common methods of a multivariate statistical analysis was applied to classify the video contents as shown in Fig. 9. This technique lays groups' samples that have similar characteristics in the same group (cluster). The objective quality scores (PSNR) that obtained from video quality evaluation from the QoS parameters listed above addition to LTE scheduling algorithm were applied as an input to the cluster analysis tool that classifies the video content into four types.

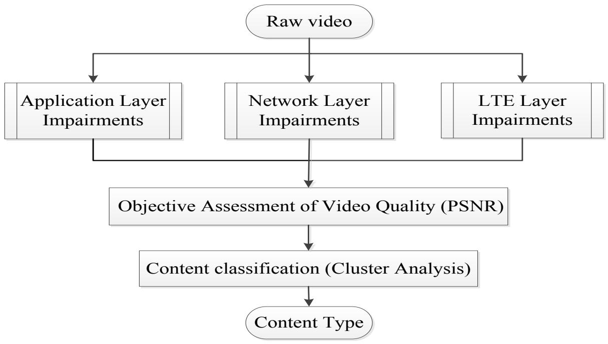

Fig. 9. Content Classification Model

The hierarchical cluster analysis was used to classify our data, so the video clips that have the nearest Euclid distance are grouped together in the same cluster as shown in Fig. 10 (dendrogram). Based on Sturge's rule ($k = 1 + 3.3 \, Log \, N$) [21], where (N) is the number of video clips. If we apply this equation to our data, k = 4, we will have four groups. As shown in Fig. 10, the data contains a clear structure in terms of clusters that have similar attributes with a slight difference in the degree of similarity between the elements of each cluster as indicated by the dotted line.

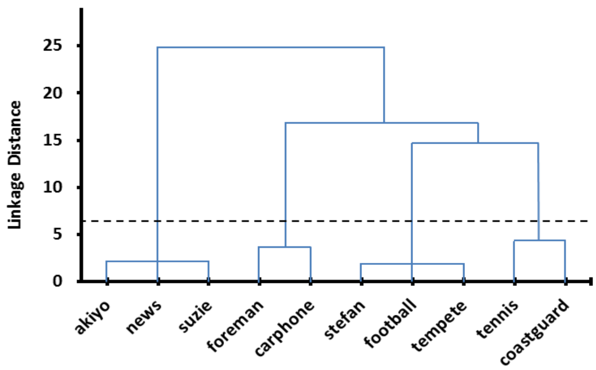

Fig. 10. Hierarchical Cluster Analysis

The Hierarchical cluster analysis in Fig. 10 illustrated that the selected video clips were grouped into four clusters according to content type: Low Motion (LM), Medium Motion (MM), High Motion (HM) and Rapid Motion (RM). The correlation coefficient (cophenet) was used to determine the defacement of our data classification given by cluster analysis method. The value of the cophenet should be very close to 100% for a high-quality solution which shows how readily the data fit into the structure proposed by classification methods. In our classification, the cophenet was (84.96%), which indicates an excellent classification result.

The classification used in this study is exclusive to this research, and it encompasses four of the most frequently used contents for video transmitted over wireless networks which are classified as below:

- First type – **Low Motion (LM):** contains video clips which have a slight moving region of interest (face and shoulder with a static background), e.g. news type (sequences Akiyo, Suzie, and News).
- Second type – **Medium Motion (MM)**: contains video clips which have contiguous scenes unstable in the background (face and shoulder with a dynamic background), e.g. video call (sequences Carphone and Foreman).
- Third type – **High Motion (HM):** contains video clips which have a wide-angle sequence where the motion includes most parts of the picture, e.g. individual sports (sequences Coastguard and Tennis).
- Fourth type – **Rapid Motion (RM):** contains video clips which have a professional wide-angle sequence where the motion includes the entire picture parts uniformly, e.g. team sports (sequences Stefan, Tempete, and Football).

4.3. Evaluation of our classification vs. common methods

The most common method to classify video clips is according to their spatiotemporal features [21]. Therefore, to classify video clips based on this method and its intricacy of content, the spatiotemporal grid divides each video clip into four varieties based on its spatial and temporal features, as shown in Fig. 11. When we compared our content classification based on PSNR scores with correlation (84.96%) and the classification in [31] based on the MOS scores with correlation (73.29%) to the common method of classification by spatiotemporal grid based on feature extraction in [32] with correlation (88.1%), a significant correlation between our classification and the spatiotemporal grid was found.

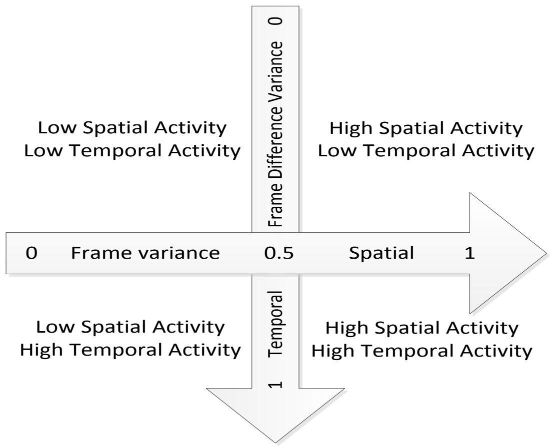

Fig. 11. The Spatio-Temporal Grid

4.4. Degree of Influence of Quality Parameters

Principal component analysis (PCA) was implemented to determine the degree of impact of each video quality parameter that used to classify video content. PCA is a method of data decrease aimed at obtaining a small set of derived variables which can be utilized instead of the larger set of original variables to simplify subsequent analysis of the data. There are two types of PCA: a covariance matrix used in the case where the same data share a single set of variables, and a correlation matrix used in the case where the data has different sets of variables. In this work, the type of a covariance matrix was used because our data has the same set. PCA was carried out to identify the relationship between video quality assessments (PSNR/MOS) and related parameters. The PCA was performed for the four video content types of LM, MM, HM, and RM separately. The PSNR correlation coefficient I matrix of the four content types is shown in Table 5. The value of the correlation coefficient is such that $-1 < r < +1$. The (+) and (–) signs are used for positive linear correlations and negative linear correlations, respectively. The PCA scores of each quality parameter are given in the columns in the above table. A higher score value, regardless of the sign (+) or (–), means that the parameter has a higher impact. Table 5 demonstrates the impact of each quality parameter on video quality. This can be seen all the values of SBR are positive and the values of PLR, FR, and RES are negative. This means that the SBR has a positive impact (when the value of SBR increases, the quality increases too), while the other variables have the opposite effect (when the values of PLR, FR, and RES increase, the quality decreases). These findings confirm the results obtained in the section IV-A.

Table 5. PSNR Correlation Coefficient Matrix

Content Type	Clip Name	FR	SBR	RES	PLR
LM	Akiyo	-0.257	0.439	-0.387	-0.711
	Suzie	-0.429	0.647	-0.261	-0.506
	News	-0.417	0.429	-0.381	-0.640
MM	Foreman	-0.179	0.343	-0.507	-0.724
	Carphone	-0.246	0.512	-0.527	-0.568
HM	Tennis	-0.434	0.659	-0.489	-0.299
	Coastguard	-0.370	0.454	-0.465	-0.606
RM	Football	-0.475	0.596	-0.335	-0.479
	Stefan	-0.410	0.644	-0.514	-0.295
	Tempete	-0.462	0.728	-0.331	-0.327

Another interesting finding in the PCA scores is that SBR and PLR parameters for video contents have a higher impact than FR and RES parameters for video contents. Moreover, in the LM category, higher PLR had a greater impact on video quality than SBR, FR, and RES. In contrast, in the RM category, SBR had a bigger impact on video quality than other parameters. The findings of this work could be used to help in understanding the behavior of video streaming over LTE networks. It can contribute to the design of accurate models to predict the video quality and to develop control schemes to optimize values of these parameters in order to achieve the best quality for the video streaming over LTE networks.

5. The proposed Scheme

The aim of this work is to develop content-aware and QoE optimization scheduling of video streaming applications over LTE networks. As shown in Fig. 12, the proposed scheme consists of QoE-based prediction model using RNN technique, optimization model based on GA, scheduler, and transmitter. Through the QoE database that obtained above from experiments simulation, the RNN models were trained based on existing LTE scheduling algorithms so that models become able to predict the specific outputs of the network. Accordingly, the GA will generate new populations and evaluate their fitness using RNN prediction model to define the optimal input parameters of the network system. This scheme was designed to obtain maximum QoE and throughput while maintaining fairness among users. Moreover, it is possible to add different extra parameters like QoS, queue length, SINR, etc. based on network system requirements.

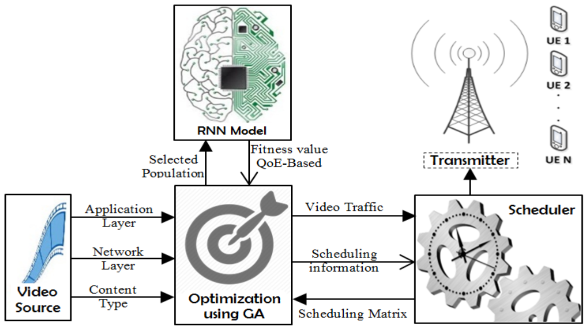

Fig. 12. The block diagram of the proposed scheme

5.1. RNN prediction model

The most significant QoE parameters were identified as the input variables for RNN prediction model. Appropriate RNN architecture and a training algorithm were selected using MATLAB framework [33] and C++ language. The architecture of RNN consisting of a four feed-forward layers; input layer has six neurons corresponding to the input parameters (SBR, SM, target Delay, Speed, UE, and CT), output layer has three output neurons corresponding to MOS, throughput and fineness, and two hidden layers; each layer has eight neurons, as shown in

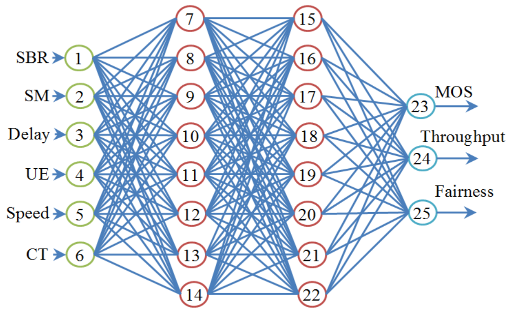

Fig. 13. The QoE database obtained above in the subsection 3.3 was divided randomly into two sets: the first set was used in training stage while the second set was used in testing prediction accuracy. Our RNN prediction models were trained with a gradient descent (GD) training algorithm and tested using an untrained dataset.

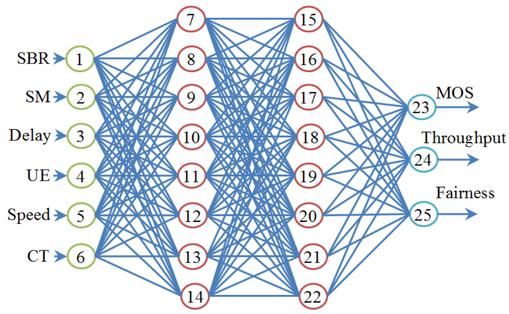

Fig. 13. The proposed RNN based model

5.2. GA Optimization Model

Unique integration between optimization techniques (GA) and artificial intelligence (RNN) to maximize QoE over LTE networks has been developed. As shown in **Error! Reference source not found.**, the flowchart illustrates the integration process of GA with RNN to optimization scheduling algorithm of the video stream. The process begins by identifying the network system input parameters with their boundaries. The system input variables are composed of the network, application, and LTE layer parameters and divide into two categories, either controlled or uncontrolled variables. The control parameters are the targets (like SBR, SM, RES, FR, bandwidth and target delay) that the system is to respond for achieving a fitness function (like maximize QoE, throughput, and fairness, minimize delay and PLR).The next phase will include the development of the GA population of the input network system parameters for use in the probabilistic-based optimal search followed by QoE prediction function using RNN-based model. In the communication network system, the fitness function ordinarily related to the cost of QoE (e.g. MOS) or QoS (e.g. throughput, PLR, and fairness). The fitness function evaluates the quality of each individual in the population at each iteration. There are several methods in [34] and [35] can be used to evaluate the fitness of a given individual. In this work, the value of the MOS function was chosen as QoE fitness value for each individual. When the QoE output is available by the RNN-based prediction model, it passes to the cost function to calculate the new fitness value and compares to relevant previous outputs. The fitness requirements are updated from time to time according to the cost function, at the same time a new generation of the population will be produced and will be going through the same evaluation process of previous generations. The same process continues until achieving a certain condition or reaching the maximum number of generations. The population of the generation groups that has the highest cost of fitness is rewarded the final generation and selected as the winner [36]. The procedure can be summarized in the algorithm below:

Algorithm 1 A Genetic Algorithm with RNN	
1.	**Input:** lower bound and upper bound of each parameter;
2.	**Set** random initial population of ***n*** chromosomes;
	While the final condition was not met **do**
3.	Compute the fitness ***f(x)*** of the population using RNN model;
4.	Evaluate the ***f(x)*** of each chromosome ***x*** in the population;
	if the ***f(x)*** value is the best? **Then**
5.	**Set** the population as Fitness winner;
	end if
	if not final generation? **Then**
6.	Create new population:
	Selection of parent chromosomes ‘roulette’;
	Crossover to produce children ‘new offspring’;
	Mutation of children ‘mutated offspring’;
	Place new offspring in the new population;
	else
7.	**output**: Fitness winner;
	end if
	end While

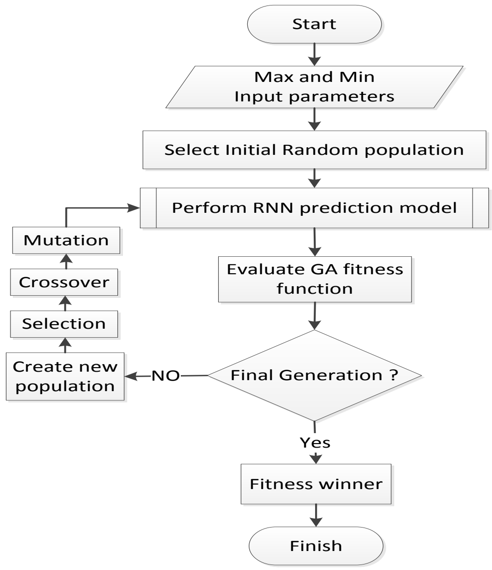

Fig. 14. Optimization schema based on RNN and GA

In the optimization process, the outputs of the GA should be the optimal set of network system input parameters i.e. SBR, SM, Target Delay, Speed and Users number (UE) to maximize QoE while maintaining fairness. In a practical and detailed, the GA program works as follows:

1) Initialization, an initial population of chromosomes is randomly created and can be any desired size. In our work, 100 populations were selected, which is a trade-off between an efficient searching process and the avoidance of premature convergence. The initial population was created within the assigned input constraints as follows: scheduling metric (SM) type from 1 to 6 as shown in Table 2, SBR from 128 kb/s to 880 kb/s, target delay from 0.04s to 0.1s, speed from 3km/h to 120km/h, a number of users from 10 to 30 (UE) and four types of video stream (CT). The input parameters of the population were converted from decimal to binary format using C++ code.
2) Evaluation, during this operation each chromosome in the population is evaluated by calculating a fitness for that individual using the RNN predicted model to the decoded sequences of the variables. The results were obtained for the entire population and compared to give the ranked fitness values.
3) Selection, the main idea of selection operation is to continuously improve population overall fitness population by discarding the poor designs and only passing the best individual chromosomes in the population to the next generation. There are several selection methods, but the basic idea is the same, the roulette wheel method was applied to select a new population as shown in Fig. 15. Chromosomes with better fitness values occupy a larger block and will have a bigger chance to be selected in the new offspring.

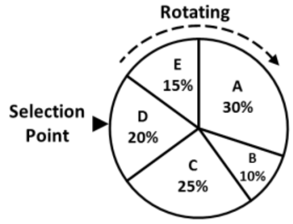

Fig. 15. Roulette wheel selection

4) Crossover, during crossover new individuals, is created by combining aspects of two or more selected individual

chromosomes. In our work random points along the strings of chosen individual chromosomes were selected then exchange the values at these points as shown in Fig. 16. The goal is that by combining certain traits from two or more individual chromosomes will create a new offspring which will inherit the best traits from each of its parents.

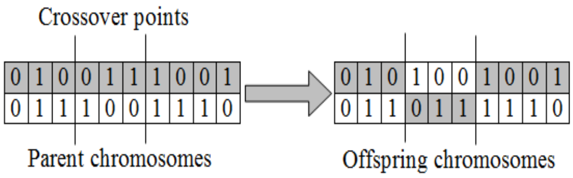

Fig. 16. Two-point crossover

5) Mutation, this operation typically works by making very small changes at random to individual chromosomes, in our work one of the bits of the new individuals was changed from 0 to 1. Its purpose is to maintain diversity within the population and prevent premature convergence as shown in Fig. 17.

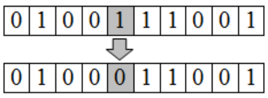

Fig. 17. Binary chromosomes mutation

6) Repeat, after new generation was generated cyclic repetition of the above steps 2 and 3. The algorithm will stop after a fixed number of iterations based on the maximum number of generations.

6. Results and Discussion

6.1. QoE prediction model

This section presents a detailed analysis of the results obtained from the RNN-based model. We studied the impact of video content types on perceived video quality, next compared the results achieved by the objective method based on PSNR for the four content types to our RNN models. Figures 18-21 show the comparison of outputs from the RNN models we implemented with PSNR metric. These figures compare the results of PSNR based on a trained RNN to the test-bed PSNR measurements of the four different video files in the same content type. The validation of the results of the proposed content-based RNN, in terms of the RMSE and Pearson correlation coefficient between the predicted and measured PSNR for the four content types, are given in Table 6. The introduction of a content type with application and network related parameters as an input to the content-based RNN models produced much closer results to objective values (real world) compared to previous models [37] and [38] in terms of RMSE and correlation coefficient. The overall RNN performance of the two hidden layers for feed-forward architecture is much closer to PSNR values of objective references points than for other architectures. This indicates our RNN model is predicting the PSNR of sample video signals very accurately. The results demonstrate that the RNN models have the ability to learn quickly from the changes in input data and that they are more efficient and accurate.

Table 6. Validation results of RNN models

Content Type	Correlation coefficient		RMSE	
	Our RNN	ANFI [37]	Our RNN	ANFIS [37]
LM	0.80563054	0.7007	0.0866	0.1545
MM	0.92364838	0.8056	0.0933	0.1846
HM	0.820923722	0.754	0.0781	0.5659
RM	0.955947722	0.754	0.0818	0.5659

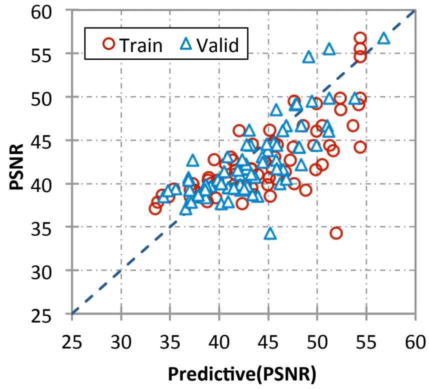

Fig. 18. RNN mapping of predicted PSNR for LM

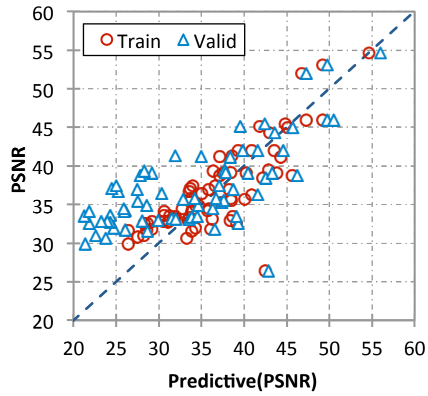

Fig. 19. RNN mapping of predicted PSNR for MM

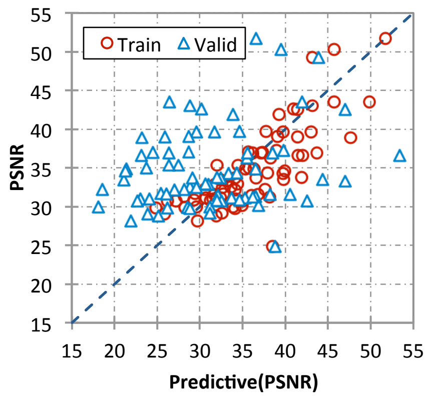

Fig. 20. RNN mapping of predicted PSNR for HM

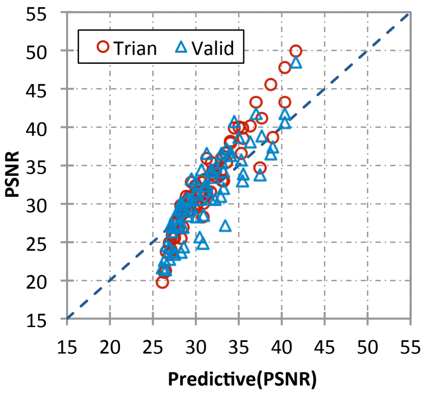

Fig. 21. RNN mapping of predicted PSNR for RM

6.2. QoE Optimization model

In this section, QoE optimization scheduling algorithms based on RNN and GA was introduced. The performance of RNN-GA optimization scheduling was analyzed and compared with the most common LTE scheduling algorithms (EXP rule, LOG rule, and FLS) in terms of QoE. The proposed framework was tested and evaluated using varying the number of users from 10 to 30, and three different speeds (3, 30, and 120 km/h) to real-time video traffic. The comparison was based on the performance of the QoE of MOS, throughput and the fairness issues for different content types; (LM, MM, HM, and RM) of the video stream. The quality of received video stream was estimated computing the MOS between the transmitted and the received video streaming over LTE networks. MOS considers one of the key metrics for QoE evaluation in real-time streaming of video applications. Fig. 22 shows the MOS computed for the video streaming, as expected, the MOS is dropping by raising the user's number and speed. However, the most important result was obtained is that the proposed scheduler can achieve the best video quality in terms of MOS under all different conditions with all content types. In general, the proposed scheme can guarantee an MOS gain up to about 3.7 in scenarios having speed up to 30 km/h. According to ITU-T Recommendation P.910 [39], the MOS score equal to 3 or higher corresponds to satisfaction for all users with respect to EXP rule, LOG rule, and FLS schedulers.

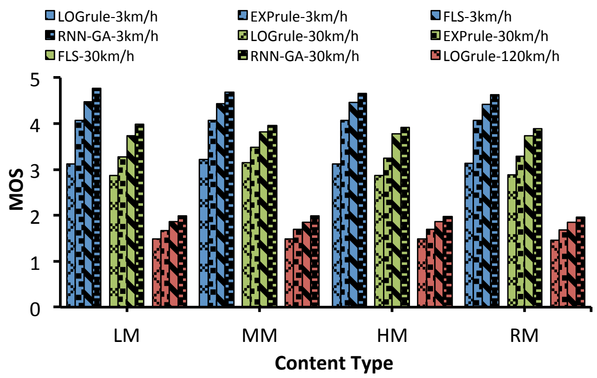

Fig. 22. MOS comparison with four CT

In general, throughput is the amount of data transferred successfully from transmitter to receiver in a given time period and typically measured in bits per second (bps). Fig. 23 shows the comparison of average throughput between proposed scheduler and state-of-the-art LTE schedulers; it is easy to observe that the achieved throughput of RNN-GA optimization scheduler was the best among all schedulers, thanks to the optimal choice of system parameters. Through the study of behavior aggregate throughput of video flows under different conditions over LTE networks, we also observe that the throughput of our proposed scheduler was increased steadily with all content types of video traffic.

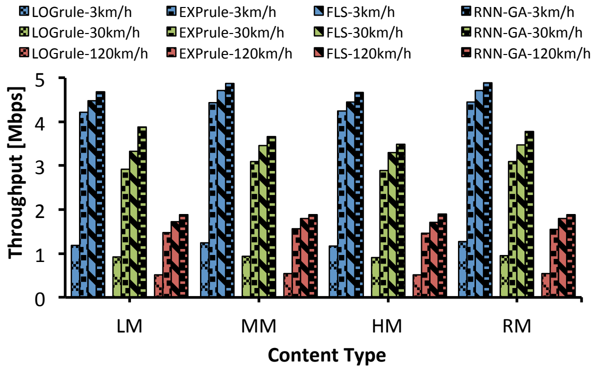

Fig. 23. Throughput of video flows with four CT

In addition to above, the fairness is one of the key functions of scheduling and should be taken into account when designing any algorithm. In more detail, a scheduling algorithm should be fair in the sense that, in addition to warranty a QoE optimization, it is important to ensure that a fair manner distribution of available resources to all network users, and do not allow achieving good results for some users at the expense of others. Fairness index is a key performance metric to use significantly to measure the fairness, the range value of fairness index is between 1 and 0, the fairness values closer to 1 the index of a metric is the fairer a discipline and vice versa [40]. As shown in Figures 24-26, RNN-GA scheduling algorithm under three different speeds provides a slightly more fairness among state-of-the-art LTE downlink scheduling algorithms that reported in [23]. This indicates that RNN-GA optimization scheduler works best compared with other scheduling models.

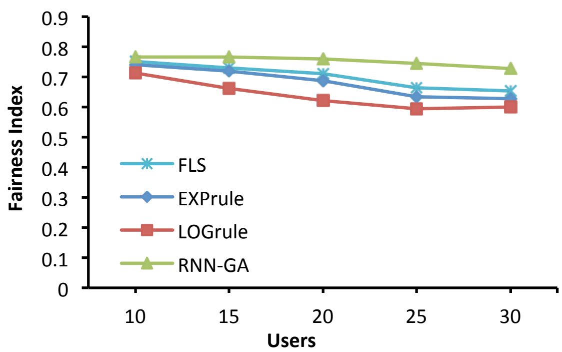

Fig. 24. Fairness of video flows with speed 3 km/h

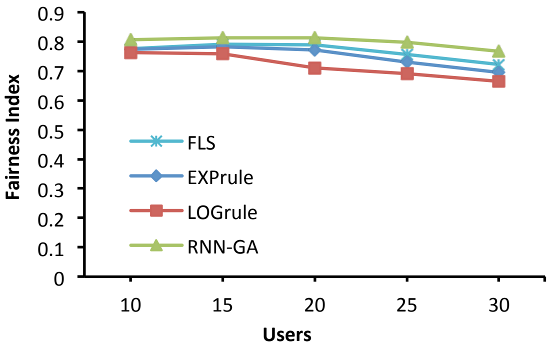

Fig. 25. Fairness of video flows with speed 30 km/h

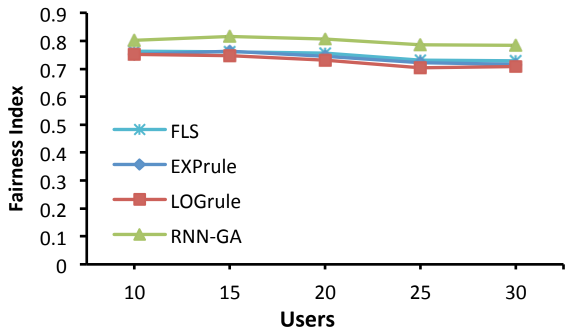

Fig. 26. Fairness of video flows with speed 120 km/h

7. Conclusion

In this study, the design of a novel content-aware and QoE optimization algorithm of video streaming over LTE networks was formulated. Video contents have been classified into four groups based on intrusive objective assessment obtained from quality parameters in the application, network, and LTE-related layers using hierarchical cluster analysis. The design requires the new optimization scheduling algorithm which is an integration of applied GA together with RNN to identify the optimal CT with global optimal input parameters which target maximizing QoE without compromising fairness among network users. The strength of this integration is to provide one with the compound ability of GA whose function is to ensure a quick search choice within the bounded parametric space, and RNN whose function is to learn complex nonlinear mapping of QoE. The comparative analysis of the performance from a range of design scenarios shows clearly that RNN-GA integration obtains better QoE and fairness performance over FLS, EXP-rule, and LOG-rule schedulers. The results from the simulations show about 15% increase in performance; this suggests that content-aware QoE optimization proposal framework is not only better based on performance but also better based on throughput. Applying different optimization algorithms like evolutionary algorithms, Convex Algorithms is potentially one direction for the future research in this area. Another possible route is to develop optimization LTE-uplink scheduling algorithms using GA integrated with QoE prediction models.

Abbreviations

Terminology	Meaning
AMC	Adaptive Modulation and Coding
BLER	Block Error Rate
CAGR	Compound Annual Growth Rate
CQI	Channel Quality Indicator
CT	Content Type
DPS	Delay Prioritized Scheduling
FDPS	Frequency Domain Packet Scheduling
FLS	Frame Level Scheduler
GA	Genetic Algorithm
HM	High Movement
LM	Low Movement
LTE	Long Term Evolution
MCS	Modulation and Coding Scheme
M-LWDF	Modified Largest Weighted Delay First
MM	Medium Movement
MOS	Mean Opinion Score
MQAF	Multi-QoS Aware Fair
nRT	Non-Real Time
OSI	Open Systems Interconnect
PDCCH	Physical Downlink Control Channel
PDSCH	Physical Downlink Shared Channel
PF	Proportional Fair
PLR	Packet Loss Rate
PSS	Priority Set Scheduler
QCI	Quality Class Identifier
QoE	Quality of Experience
QoS	Quality of Service
QoSP	QoS Provide
RB	Resource Block
RM	Rapid Movement
RMSE	Root-Mean-Square Error
RNN	Random Neural Network
RT	Real Time
SBR	Send Bit Rate
SINR	Signal-to-Interference-plus-Noise Ratio
SM	Scheduling Matrix
TDPS	Time Domain Packet Scheduling
TTI	Transmission Time Interval
UE	User Equipment

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