

Two-Pass Video Rate Controller with Globally Optimal Rate-Distortion and Buffer Constraints for Variable Bitrate Applications of H.266/VVC

Arshnoos Nakhaei¹ | Mehdi Rezaei² | Mahdi Kazemini³

University of Sistan and Baluchestan, Department of Communications Engineering, Zahedan, Iran.^{1,2}
Velayat University, Faculty of Electrical and Computer Engineering, Iranshahr, Iran
Corresponding author's email: mehdi.rezaei@ece.usb.ac.ir

Article Info	ABSTRACT
Article type: Research Article Article history: Received: ***** Received in revised form: ***** Accepted: ***** Published online: ***** Keywords: Genetic Algorithm; H.266/VVC; Video Rate Control; Optimization; Two-pass.	This paper introduces a two-pass rate control algorithm tailored for offline variable-bitrate applications that conform to the H.266/VVC standard. In the first pass, a rate controller at the group-of-pictures (GOP) level is used for encoding to collect the data required for the second pass. In the second pass, a Genetic algorithm (GA) directly determines optimal quantization parameters for all GOPs in the sequence simultaneously. It minimizes a global sequence-level rate-distortion (R-D) objective function while ensuring adherence to the buffering constraints. In fact, it uses the available buffer space to provide optimal bitrate variations, thereby minimizing rate-distortion. The proposed controller is implemented in the VVC test model (VTM) and evaluated against several benchmarks. Experimental results demonstrate that the proposed method achieves superior performance on the R-D objective function used in the GA. This achievement includes significant bitrate reductions and quality improvements while adhering to the buffering constraint. Moreover, the proposed controller achieves a more stable quality, resulting in higher visual quality for the reconstructed video.

I. Introduction

The most recent video compression standard is the versatile video coding, also known as H.266/VVC. It significantly improves compression efficiency, providing up to 50% reduction in bitrates compared to the previous one, while maintaining the same subjective quality [1-3]. This versatile standard is designed to improve coding quality across diverse video applications, including live and non-live scenarios. In a live scenario, video content is coded and transmitted immediately through communication channels. However, encoded video content is stored in storage devices before transmission in a non-live scenario. Nevertheless, the transmission of encoded video over communication networks faces various fundamental issues, such as limited bandwidth, transmission delays, and buffer constraints. Therefore, efficient rate control (RC) mechanisms are implemented during encoding to overcome these challenges. They aim to facilitate the efficient transmission of encoded

video data while providing acceptable perceptual quality [4, 5].

Given the wide variety of applications supported by the VVC standard with varying latency requirements, employing effective RC methods is indispensable. This issue has led to the development of two primary categories of RC algorithms: constant bitrate (CBR) and variable bitrate (VBR). CBR controllers are optimized for low-latency applications and operate at lower control levels. In contrast, VBR controllers are designed for high-latency scenarios and operate at higher control levels. The RC level is defined here as the lowest coding level in the bit allocation process, for which the Quantization Parameter (QP) is set to control the bitrate. These control levels include scene, Group of Pictures (GOP), frame, Coding Tree Unit (CTU), or Coding Unit (CU). They enable RC algorithms to be effectively tailored to various operational scenarios.

Generally, the RC level is determined by the application's latency constraints. Low-level control mechanisms are essential for low-latency scenarios to ensure a constant bitrate. Conversely, higher-level control schemes are typically preferred in high-latency applications to minimize unnecessary fluctuations in the quality of the encoded video at lower levels.

From the perspective of the number of encoding passes, RC algorithms are typically categorized into three modes: one-pass, pre-encoding, and two-pass. One-pass rate controllers dynamically control the bitrate throughout the encoding process. Hence, they are well-suited for real-time scenarios such as video conferencing. Numerous RC algorithms have been proposed for the VVC standard, with the most adopted one-pass architectures targeted at real-time applications [6-26]. More specifically, the CBR algorithms in [6-15] operate at the CTU level and target low-delay applications. Those in [16-20] operate at the frame level and target medium-delay applications. Conversely, VBR algorithms proposed in [21-25] and [26] are suitable for high-delay applications and operate at the GOP and scene levels, respectively. Pre-encoding RCs involve lightweight pre-analysis and encoding over a limited temporal window. This process gathers content characteristics before final encoding. These controllers are particularly effective in applications that tolerate delays beyond real-time, such as video surveillance systems. As examples of pre-encoding RC algorithms, the algorithms presented in [27, 28] are CBR algorithms tailored for the VVC standard. Two-pass rate controllers encode a video sequence in two passes, using information from the first pass to improve the second pass's encoding quality.

In many two-pass approaches, first-pass information is further used to solve a constrained optimization problem for the second pass of RC. The corresponding objective function can be formulated in various ways according to the target application. Possible objectives include rate-distortion (R-D) minimization, perceptual quality maximization, or temporal quality consistency. Each objective can be subject to a distinct set of operational constraints, such as target bitrate and buffer occupancy. Crucially, the optimization-based RC is conceptually and operationally distinct from the conventional R-D optimization (RDO) process embedded in modern video codecs. RDO is solely concerned with selecting coding decisions such as prediction modes, partition structures, and transform configurations. Generally, an RC algorithm determines the QPs that control the rate, while the RDO process provides the optimal modes for the given QPs to minimize the rate-distortion.

Two-pass RC is particularly suited to offline or non-real-time applications such as broadcasting and video-on-demand applications, where computational complexity and encoding time are less critical constraints.

II. Related Works

Two-pass RC strategies yield highly efficient R-D performance, but they have been less investigated than one-pass approaches. The CU-level rate controllers described in [29-31] and the scene-level RC in [32] employ two-pass algorithms to control bitrate efficiently. The RC algorithm presented in [30] is the completed version of that in [29]. It is proposed for the HEVC standard and implemented within the HM reference software [33]. It employs an SSIM-based perceptual criterion to construct a perceptually uniform quality video. In the first pass of this algorithm, the video sequence is encoded in the constant QP (CQP) mode. The resulting statistics are used to establish Laplacian-based rate and perceptual distortion models for adaptive bit allocation. Subsequently, in the second pass, the adaptive bit allocation process is formulated as an optimization problem. It minimizes sequence-level distortion while keeping the sequence rate below a limit. This optimization provides the optimal number of bits for each GOP. Then, GOP bits are used for bit allocation at the frame. Then, the R-D model is used to compute QPs at the frame and CU levels. In this algorithm, the target bits at the frame level are updated based on the buffer status. This causes deviation from the optimal values [30].

More recently, [31] introduced a VBR RC scheme tailored for the VVC standard. The method was implemented on VVenC, a production-oriented encoder that trades off advanced coding tools for computational speed. This approach incorporates a CTU-level refinement stage to improve perceptual quality, based on the low-complexity XPSNR metric. In the first pass, a CQP-based encoding is used to collect frame-level statistics, including QP values, Lagrange multipliers, and bitrate information. During the second pass, an empirical R-QP model is used to estimate and refine the QP for each frame based on the target bitrate and the bits produced in the first pass. Subsequently, block-level QP refinements are performed based on XPSNR-derived perceptual weights and the estimated frame-level QP. This algorithm incorporates the XPSNR-driven perceptual criteria for the RDO process and also for the bit allocation at the block level, while a simple bit allocation method at the frame level is used. Although this is acceptable for the CBR rate-control scenario, it is not optimal for the VBR rate-control scenario, where optimal variations in bitrate are desired.

The RC proposed in [32] is an example of a two-pass VBR algorithm for the HEVC standard, evaluated within the HM reference software. In this approach, first-pass encoding by a VBR rate controller provides statistics required for a constrained optimization task in the second pass. Specifically, the optimization determines the best QP for

encoding a scene in CQP mode while minimizing bitrate error at the scene level. This task employs a simplified Lambda-domain R-D model and a greedy search strategy to determine a QP for each scene. While this method enhances perceptual quality through CQP encoding at the scene level, it may result in coarser control and longer buffering delays, particularly for extended video scenes. This algorithm provides scene-wise optimal QPs, but they are not optimal globally at the sequence level.

This investigation focuses on developing a VBR RC algorithm tailored for offline VVC applications. In a new approach, recognizing the CQP encoding as the best method in terms of R-D performance and perceptual quality under uncontrolled bitrate variations, the proposed algorithm seeks optimal bitrate variations that closely match those of the CQP encoding while adhering to buffer constraints. This approach employs a two-pass GOP-level RC algorithm. Initially, in the first pass, the video sequence is encoded using the Fuzzy-Proportional-Integral-and-Derivative (FPI-D) RC algorithm proposed in [25]. The encoding statistics of all frames are then collected. In the second pass, a Genetic algorithm (GA) directly determines optimal QPs for the entire GOPs of the sequence simultaneously. The optimization minimizes a global sequence-level R-D objective function while ensuring adherence to buffer constraints. The optimal base QPs are combined with a QP-cascading algorithm for second-pass encoding. They may be slightly modified through neighboring one-step QP adjustments. This GOP-level approach improves visual quality stability by avoiding short-term QP variations. Additionally, this GOP-level RC facilitates computationally complex optimization that would be prohibitive at lower control levels, such as frame or CTU levels.

To provide a concise comparative overview of existing two-pass RC strategies and to clearly illustrate the advancements of the proposed framework, the main characteristics of the reviewed approaches are summarized in Table I. These benchmarks include the target coding standard, reference encoder, first-pass encoding strategy, RC optimization objectives and constraints, optimization level, and optimization output.

The main contributions of this work are as follows:

- This paper proposes a novel GOP-level RC algorithm tailored for VBR applications of the H.266/VVC standard and implemented on the VTM reference software.
- This algorithm controls the bitrate in two passes and is suitable for non-live video encoding.
- Unlike the previous two-pass algorithms that used CQP encoding in the first pass [29-31], we used a VBR rate controller to enhance consistency between the QPs calculated across both encoding passes. This decreases the inaccuracy effect of the R-D model used in the optimization algorithm. Moreover, this reduces the number of iterations required by the optimization algorithm.
- The second pass employs a GA to determine the optimal base QP for all GOPs, minimizing the R-D cost subject to buffer constraints.
- Unlike previous optimization-based schemes, where buffer constraints are ignored or used independently of the optimization process, the proposed approach incorporates buffer limits directly as explicit constraints in the optimization formulation. It is worth noting that in the VBR scenario, the buffer constraints that provide long-term target bitrate are more essential than the target bitrate constraint that causes CBR.
- In a new approach, the proposed algorithm seeks optimal bitrate variations that closely match those of the CQP encoding while adhering to buffer constraints.
- While the algorithms presented in [31] and [32] execute the optimization at the frame and scene levels, which are locally optimal; our proposed optimization is executed at the sequence level and provides globally optimal results. Although the algorithm presented in [30] uses a sequence-level optimization for bit allocation, the optimal bits are later deviated by the buffer.
- Existing approaches generally use optimization for bit allocation and then use R-D models to compute QPs [29, 30]. The proposed method uses optimization to directly determine the optimal QPs. This reduces the impact of R-D model inaccuracies and deviations from optimal points.

Table I. Comparison of Two-Pass Rate Control Optimization Strategies for HEVC/VVC standards

Method	Standard/ Encoder	First Pass Encoding	Optimization Objective	Optimization Constraint	Optimization Level	Optimization Output
[29], [30]	HEVC/ HM	CQP	Maximizing SSIM-based perceptual quality	Sequence bitrate	Sequence	GOP Bit Allocation
[31]	VVC/ VVenC	CQP	Minimizing XPSNR-based distortion	Frame bitrate	Frame	Block Bit Allocation
[32]	HEVC/ HM	Frame-level RC	Minimizing scene-level bitrate error	Constant QP scene	Scene	Scene-level QP
Proposed	VVC/ VTM	GOP-level RC	Minimizing sequence-level R-D	Buffer constraints	Sequence	Sequence-level GOP QPs

- In the proposed algorithm, the encoding simulation results of the optimization algorithm and the actual encoding results in the second pass closely match. This proves that the actual results of the proposed algorithm are indeed optimal.

The remainder of this paper is organized as follows: Section 2 details the proposed rate controller. Section 3 shows the experimental results, and Section 4 concludes the paper.

III. Proposed Rate Controller

In this paper, an optimal two-pass RC algorithm tailored for high-delay applications of the VVC standard is proposed. Both passes of the algorithm are detailed in the sequel.

A. First-Pass

The block diagram of the proposed RC algorithm used in the first encoding pass is shown in Fig. 1. The essential components of the algorithm include a virtual buffer, a fuzzy PI-D rate controller, and a QP-cascading model. In this approach, given the high content correlation between successive GOPs, the base QP of the previous GOP, Q_{BG}^{i-1} , is used as a rough estimate for the current GOP, Q_{BG}^i . The Fuzzy PI-D controller subsequently refines this estimation, ΔQ_G , based on the buffer status and the bits consumed by the previous GOP. Following this, the QP for each frame in the GOP, Q_i , is further adjusted using the QP cascading model, taking into account parameters such as the base QP, temporal layer, and frame type. The details of these components are presented in the sequel.

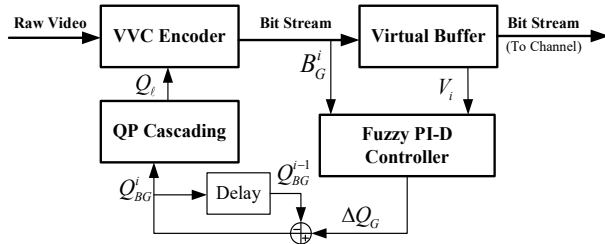


Fig. 1 Block diagram of the first pass rate control algorithm

a) Virtual Buffer

The virtual buffer simulates the behavior of the decoder buffer on the receiver side of a CBR communication channel. This buffer, which simulates the actual decoder buffer, is used for RC in the encoder and provides the buffering requirement to be signaled to the decoder at the start of video streaming. Following the encoding of each GOP, the buffer occupancy is dynamically updated as follows:

$$V_i = V_{i-1} - B_G^i + T_G, \quad (1)$$

where V_i represents the virtual buffer fullness and B_G^i indicates the bits consumed for encoding i^{th} GOP. V_0 denotes the initial buffer occupancy and is set to 60 percent of the buffer size in our experiments, as the fuzzy PI-D controller is designed to achieve optimal performance under this condition. T_G stands for GOP target bits and is calculated as:

$$T_G = \frac{T_R}{F_R} \times S_G, \quad (2)$$

where T_R stands for the target bitrate of the bitstream and F_R shows the video frame rate. S_G is the GOP size or the number of frames in a GOP.

b) Fuzzy PI-D Controller

The FPI-D rate controller is a proportional-integral-derivative controller whose objectives involve reducing the error between the GOP target and consumed bits, denoted as E_G^i . After encoding i^{th} GOP, the GOP bit error, E_G^i , is computed as:

$$E_G^i = T_G - B_G^i. \quad (3)$$

The proportional and integral components of the GOP bit error are fed into a fuzzy controller. Subsequently, the error derivative component is added to the fuzzy output, and then the resulting value is passed through a control gain to determine the outcome of the fuzzy PI-D controller, ΔQ_G . The PID components are calculated as follows:

$$E_P^i = K_P \times E_G^i = (T_G)^{-1} \times (T_G - B_G^i), \quad (4)$$

$$E_I^i = K_I \times \sum_{n=1}^i E_G(n) = (S_B)^{-1} \times \sum_{n=1}^i E_G(n), \quad (5)$$

$$E_D^i = K_D \times (E_G^i - E_G^{i-1}) = (2 \times T_G)^{-1} \times (B_G^i - B_G^{i-1}), \quad (6)$$

where K_P , K_I and K_D are the gains of the proportional, integral, and derivative components, respectively, and are set to $K_P = (T_G)^{-1}$, $K_I = (S_B)^{-1}$, and $K_D = (2 \times T_G)^{-1}$. S_B denotes the virtual buffer size.

The fuzzy controller consists of four primary modules: fuzzifier, inference engine, rule base, and defuzzifier. The fuzzifier initially maps the proportional and integral components to fuzzy input sets, and the inference module then processes this information using expert-defined fuzzy rules and fuzzy membership functions (MSFs) [25]. Then, the defuzzifier module converts the fuzzy output sets into numerical data.

The linguistic fuzzy rules and MSFs were designed empirically through preliminary coding experiments across different video content and target-rate conditions. Trapezoidal MSFs are employed for the input variables, as illustrated in Fig. 2, while symmetric triangular MSFs are used for the output variable, as shown in Fig. 3. The main

idea is to satisfy the buffer constraint while maximizing buffer utilization to reduce QP fluctuations and, in turn, quality fluctuations. The asymmetric structures in the table of fuzzy rules and the graphs of fuzzy MSFs are related to a number of facts that affect the operation of the RC algorithm. The nonlinearity of the R-D function and the difference between the bit budgets of Intra and Inter pictures are two key factors that cause the asymmetry in the structures. The other key point is that the output gain of the feedback loop depends on buffer conditions. More aggressive control is required when buffer fullness is close to critical conditions to prevent underflow and overflow, whereas looser control is preferred when buffer fullness is far from critical conditions to prevent unnecessary variations in the quality of the encoded video. After the preliminary design of the fuzzy system, a simple Greedy optimization process was performed to fine-tune the fuzzy MSFs. In the optimization process, several parameters, including average bitrate, average PSNR, average QP, and standard deviation of PSNR were considered.

Using a singleton fuzzifier, a center-average defuzzifier, and a product inference engine, the output of fuzzy controllers is computed as:

$$y = \frac{\sum_{m=1}^u \sum_{n=1}^v \gamma_{m,n} \cdot \mu_{M_m}(E_P) \cdot \mu_{N_n}(E_I)}{\sum_{m=1}^u \sum_{n=1}^v \mu_{M_m}(E_P) \cdot \mu_{N_n}(E_I)}, \quad (7)$$

where y is the output of the fuzzy controller. $\{M_1, M_2, \dots, M_u\}$ and $\{N_1, N_2, \dots, N_v\}$ are fuzzy sets with $\{\mu_{M_m}(E_P)\}_{1 \leq m \leq u}$ and $\{\mu_{N_n}(E_I)\}_{1 \leq n \leq v}$ MSFs defined for two

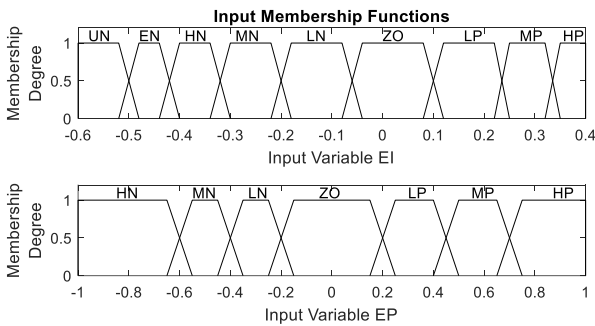


Fig. 2. Membership functions of the fuzzy inputs, EI and EP

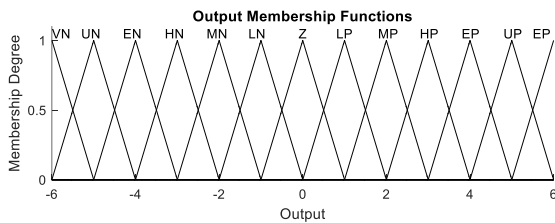


Fig. 3. Triangular membership functions of fuzzy output

inputs E_P and E_I , respectively. $\gamma_{m,n}$ denotes the center value of the fuzzy sets in the output region according to the given rule. The output central desired values are presented in Table II. More details and explanations about the fuzzy system can be found in [25].

The output of the fuzzy controller, y , is adjusted by adding the derivative component, E_D , and then the resulting value is passed through a content adaptive gain, G , to compute the output of the FPI-D controller as:

$$\Delta Q_G = G \times (y + E_D), \quad (8)$$

where ΔQ_G is the output of the FPI-D controller. The content-adaptive gain, G , can be tuned in the range of (0.5~1.5) once per video sequence. Specifically, videos with frequent scene changes and diverse scene content benefit from a higher G value, whereas videos with more homogeneous content require a smaller G value. However, it can be set to a fixed value in the middle range.

The output of the FPI-D controller modifies the base QP of the previously encoded GOP to be used for the current GOP as:

$$Q_{BG}^i = Q_{BG}^{i-1} + \Delta Q_G. \quad (9)$$

Finally, using the proposed QP cascading technique, the QP for encoding each frame within the current GOP is computed:

$$Q_\ell = Q_{BG}^i + \Delta Q_\ell, \quad (10)$$

where Q_ℓ is the QP used for encoding the frames of ℓ^{th} temporal layer. ΔQ_ℓ indicates the QP offset of the frames in the ℓ^{th} temporal layer derived by the proposed QP cascading model introduced in the sequel.

a) Proposed QP Cascading Model

The QP offset for intra-frames and inter-frames is calculated as:

Table II. Output Desired Central Values

EI	HP	-6	-5	-4	-3	-2	-1	0
	MP	-5	-4	-3	-2	-1	0	1
	LP	-4	-3	-2	-1	0	1	2
	Z	-3	-2	-1	0	1	2	3
	LN	-2	-1	0	1	2	3	4
	MN	-1	0	1	2	3	4	5
	HN	0	1	2	3	4	5	6
	EN	1	2	3	4	5	6	6
EP	UN	2	3	4	5	6	6	6
	HN	MN	LN	Z	LP	MP	HP	

$$\Delta Q_\ell = \text{round}\left(\tau\left(1 - e^{\frac{1-\ell}{\nu}}\right) - 2\right), \ell \geq 1 \quad (11)$$

where the model parameters, τ and ν , are functions of base QP and are formulated as:

$$\begin{cases} \tau = 0.0875 \times (Q_{base} - 19) + 10.01, & Q_{base} \in [20, 35] \\ \nu = -0.05 \times (Q_{base} - 19) + 2.82 \end{cases} \quad (12)$$

when the base QP, Q_{base} , falls out of the $[20, 35]$ range, the model parameters are clipped to the border values. The model details can be found in [25].

A. Second Pass

After the first-pass encoding, the frames' R-D results are collected for use in the second-pass encoding. Before the second pass, an optimization problem is solved to determine an optimal base QP for each GOP by a GA [34]. The optimization problem is formulated to minimize the normalized average rate-distortion, RD_{norm}^{P2} , subject to a constraint on the buffer fullness. This objective function is defined as the ratio of the average rate-distortion calculated for the second pass, RD_{avg}^{P2} , to that obtained during the first pass, RD_{avg}^{P1} . The optimization problem is expressed as:

$$\text{minimize } RD_{norm}^{P2} = \frac{RD_{avg}^{P2}}{RD_{avg}^{P1}}, \text{ s.t. } 0 < V_{norm}^i < 1 \quad (13)$$

where, V_{norm}^i represents the normalized buffer occupancy, $V_i \times (S_B)^{-1}$. The average rate-distortion for both passes is calculated as:

$$RD_{avg} = \frac{1}{N_F} \times \sum_{i=1}^{N_F} (D_i + \lambda_i \times B_i), \quad (14)$$

where N_F is the total number of frames in a video sequence.

D_i stands for the mean squared error (MSE) of i^{th} frame, and λ_i indicates the lambda parameter, which is exponentially related to the QP used for encoding i^{th} frame:

$$\lambda_i = e^{\left(\frac{Q_i - 13.7122}{4.2005}\right)}, \quad (15)$$

where Q_i is the QP used to encode i^{th} frame. The data required to compute the constant value of RD_{avg}^{P1} using equation (14) is collected during the first pass encoding.

The optimization problem described in equation (13) is solved using a GA-based approach. GA represents an optimization technique inspired by the principles of natural evolution elucidated by Charles Darwin [34]. As depicted in Fig. 4, the process initiates with a population of candidate solutions or chromosomes, each consisting of a distinct set of genes. These candidate solutions are iteratively refined through selection, crossover, and mutation operations, much like natural selection. A significant part of GA is the fitness

function, which evaluates solution quality and guides the selection process toward high-performing chromosomes. This iterative refinement continues until a termination criterion is met or an optimal solution is attained. Each component of the proposed GA-based approach is detailed in the following subsections.

a) Initial Population

The proposed GA leverages a novel initial population generation strategy to achieve diverse exploration of the solution space. This strategy begins by segmenting the two base QP vectors, $Q_S = [Q_{BG}^1, Q_{BG}^2, \dots, Q_{BG}^{N_G}]$, where N_G is the number of GOPs and $S \in \{p1, C\}$ denotes either the FPI-D encoding results, $p1$, or a constant QP vector, C . Each vector is divided into equal-length groups to generate candidate solutions with varying characteristics:

$$SQ_S^k = \left[(Q_{BG}^1, \dots, Q_{BG}^k), (Q_{BG}^{k+1}, \dots, Q_{BG}^{2k}), \dots, (Q_{BG}^{N_G-k+1}, \dots, Q_{BG}^{N_G}) \right], \quad (16)$$

$$\forall k = 1, \dots, 5, S \in \{p1, C\}$$

Considering the diverse characteristics of video sequences, including varying motion levels, frame complexity, and scene changes, which influence RC and QP

values, identical random noise is injected into all genes within each group to simulate the impact of these factors.

This process starts with single-gene groups, i.e., $k = 1$, and progressively increases the group size by one in each

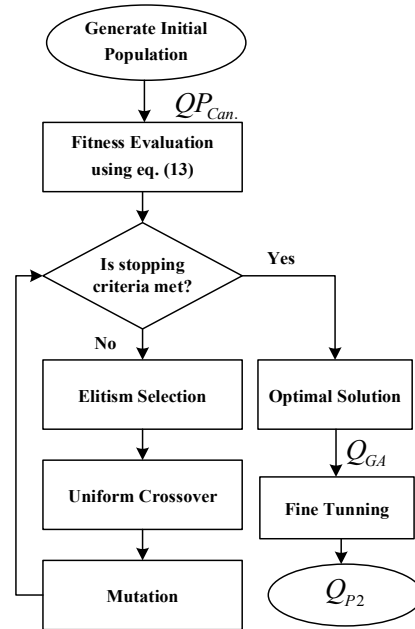


Fig. 4 The block diagram of the proposed genetic algorithm

iteration, repeated five times.

The Initial population, base QP values, derived through this strategy, are obtained by augmenting each segmented QP group with a random integer vector characterized by amplitude A and length k . The generation process is formulated as:

$$Q_{init}^{k,A} = SQ_S^k + \chi_k^A, \quad \forall k, A=1, \dots, 5 \quad (17)$$

where χ_k^A denotes a k -length vector of random integers sampled uniformly from the range $[-A, A]$. Only those initial base QPs that satisfy buffer constraints are selected as candidate solutions, Q_{can} . The initial population generation process is repeated until a sufficient number of candidates is found. In our simulations, we set this number to 350, which provides a suitable trade-off between candidate diversity and computational complexity.

b) Fitness Evaluation

The fitness function plays a critical role in the GA by assessing the quality of each candidate solution. In the proposed approach, the fitness function evaluates the normalized rate-distortion, RD_{norm}^{P2} , for a candidate solution, Q_{can} . For this purpose, the R-D models defined in the VVC standard and the data collected during the first-pass encoding are used to estimate the total bits consumed and the distortion incurred for intra- and inter-frames within a GOP. For intra-frames, a direct relationship between R and λ is formulated as:

$$\lambda_{Intra}^i = \frac{\alpha_{Intra}^i}{256} \left(\frac{1}{BPP_i} \right)^{\beta_{Intra}^i} \left(\frac{C_i}{size} \right)^{a \times \beta_{Intra}^i}, \quad (18)$$

where α_{Intra}^i and β_{Intra}^i are the model parameters for the i^{th} frame, and BPP_i is the consumed bit per pixel of the i^{th} frame. C_i represents the i^{th} picture *Sum of Absolute Transformed Differences* (SATD). Constant a is set to 1.2517, and $size$ refers to the resolution of the video frame.

Given that lambda represents the slope of R-D curves, we derive the following R-D model for intra-frames:

$$D_i = -\int \lambda_{Intra}^i dR = -\left(\frac{\alpha_{Intra}^i}{256} \right) \left(\frac{\left(\frac{C_i}{size} \right)^{a \times \beta_{Intra}^i}}{1 - \beta_{Intra}^i} \right) (BPP_i)^{1 - \beta_{Intra}^i}. \quad (19)$$

The model parameters, α_{Intra} and β_{Intra} , for each intra-frame, are calculated by jointly solving equations (18) and (19), incorporating the data collected during the first pass, P1:

$$\beta_{Intra}^i = 1 + \frac{\lambda_{Intra}^{P1,i} \times BPP_i^{P1}}{D_i^{P1}}, \quad (20)$$

$$\alpha_{Intra}^i = \left(\lambda_{Intra}^{P1,i} \times 256 \right) \left(\frac{\left(\frac{C_i}{size} \right)^a}{BPP_i^{P1}} \right)^{-\beta_{Intra}^i}, \quad (21)$$

where, D_i^{P1} , BPP_i^{P1} , and $\lambda_{Intra}^{P1,i}$ are the distortion, consumed bits per pixel, and lambda values for the i^{th} frame, respectively, collected from the first encoding pass. Similarly, the R-D model for inter-frames obtained from the VVC standard is defined as:

$$D_i = \frac{-\alpha_{Inter}^i}{\beta_{Inter}^i + 1} \times BPP_i^{\beta_{Inter}^i + 1}, \quad (22)$$

where the α_{Inter}^i and β_{Inter}^i are the model parameters for i^{th} frame, calculated as [15]:

$$\alpha_{Inter}^i = \left(BPP_i^{P1} \right)^{1 + \frac{BPP_i^{P1} \times \lambda_{Inter}^{P1,i}}{D_i^{P1}}} \times \lambda_{Inter}^{P1,i}, \quad (23)$$

$$\beta_{Inter}^i = -\frac{BPP_i^{P1} \times \lambda_{Inter}^{P1,i}}{D_i^{P1}} - 1. \quad (24)$$

During rate and distortion calculations, the lambda values for intra and inter-frames, λ_{Intra} and λ_{Inter} , are determined using equation (15). The frame QP value used in (15) is obtained by applying the QP cascading technique to the candidate solution, with an offset added to each gene as in (11).

c) Selection

Selection is a critical GA operator in which chromosomes are chosen from a population for breeding in the next generation. Here, an elitist selection strategy is employed to preserve high-performing solutions. The top 50% of chromosomes with the best fitness values are directly transferred to the next generation, bypassing the crossover and mutation operations. These ensure that random genetic operations do not compromise these elite solutions.

d) Crossover

Uniform crossover is used to generate offspring by combining genetic information from two parent chromosomes, P_1 and P_2 , to produce two offspring, C_1 and C_2 . Parents are selected at random, with one parent drawn from the elite chromosomes and the other from the entire population. For each gene, a random binary digit, $r_i \in \{0, 1\}$ determines the inheritance source:

$$C_1^i = \begin{cases} P_1^i & , \text{ if } r_i = 0 \\ P_2^i & , \text{ if } r_i = 1 \end{cases}, \quad \forall i = [1, N_G] \quad (25)$$

This pattern flips for the second offspring, C_2^i . This approach effectively explores various combinations, potentially leading to fitter offspring and improved solutions over generations.

e) Mutation

To prevent the population from converging on local minima, a mutation operation is applied to a portion of the offspring chromosomes at a predefined mutation rate of 0.3. The mutation rate of 0.3 was empirically determined, as lower values tended to reduce population diversity and increase the risk of premature convergence. In contrast, higher values disrupted the propagation of high-quality solutions. A specific percentage of genes within each chromosome is then randomly selected and mutated by adding random noise. The mutation operation is formulated as follows:

$$MC_j = \begin{cases} C_j^i + n & , \text{if } g < 0.1 \\ C_j^i & , \text{otherwise} \end{cases}, \quad \forall i = [1, N_G], j \in \{1, 2\} \quad (26)$$

where MC_j indicates the j^{th} mutated offspring. The mutation parameters, n and g were empirically optimized through extensive experiments. The random integer n in the closed interval $[-1, 1]$ introduces minimal, localized perturbations, allowing fine-tuned exploration around candidate solutions. The mutation probability g represents a random float value in the closed interval $[0, 1]$ to achieve the best trade-off between preserving good solutions and maintaining enough diversity to avoid premature convergence.

f) Stopping Criteria

The stopping criterion in the proposed GA framework is defined using a hybrid approach that balances optimization accuracy and computational efficiency. The optimization process is terminated when either the maximum configuration of 200 generations is reached, or the relative improvement of the best objective function value over 60 consecutive generations falls below a threshold of 10^{-4} . Although convergence was typically achieved around 100 iterations, extending to 200 provided minor yet consistent improvements, while further increases had a negligible effect. This extended 60-generation window enables the GA to detect practical convergence while allowing sufficient opportunity to escape temporary local optima. Upon reaching this threshold, the chromosome with the lowest fitness value is recognized as the globally optimal solution, Q_{GA} . The solution may be further refined through a fine-tuning step. During fine-tuning, each gene of Q_{GA} is incremented and decremented by one to generate neighboring solutions. The fitness values for these adjustments are then calculated. Among Q_{GA} and its

neighboring solutions, the one exhibiting the lowest fitness value is selected as the final optimal base QP, Q_{P2} , for the second-pass encoding.

IV. Simulation and Experimental Results

The proposed rate-distortion optimization two-pass rate controller (RDOTP) was implemented on the VTM-15.1 standard reference software to evaluate its performance [35]. The experiments were conducted under the Random Access (RA) configuration with a GOP size and Intra-frame period of 16. Unlike CBR RCs, which focus on short-term bitrate control, VBR RCs, such as RDOTP, provide long-term bitrate control. Consequently, long test sequences are required to comprehensively evaluate the performance of VBR RCs.

We concatenated several well-established short test sequences presented in [36, 37] to create five long test sequences for evaluating the proposed RC algorithm. Each sequence has a frame rate of 60fps. The first sequence, LV1, consists of 1201 frames created by concatenating the BQMall and BQTerrace sequences at the 832x480 resolution. Sequences LV2 and LV4, each containing 1185 frames, were formed by concatenating the FourPeople and Vidyo3 sequences at resolutions of 832x480 and 1280x720, respectively. Similarly, sequences LV3 and LV5, comprising 1185 frames each, combined the KristenAndSara and Johnny sequences at the same resolutions.

This paper comprehensively evaluates the performance of the proposed rate controller utilizing various metrics, including R-D performance, bitrate control accuracy, and quality fluctuation. For performance comparison, the test sequences were encoded using the CQP method, a well-regarded technique for generating high-quality videos. Additionally, the evaluation incorporates the RC algorithm implemented within the VVC reference software, VTM-15.1 (VTM-RC). This rate controller leverages a lambda-domain R-D model and accounts for hypothetical reference-decoder considerations. It therefore provides a baseline for cross-verification with a wide range of RC algorithms within the VTM framework. Finally, the Fuzzy PI-D (FPI-D) RC, used in first-pass encoding, was also included. Moreover, the GA results obtained based on the simulations (Simul) are considered for deeper analysis. All test sequences were encoded using CQP with fixed QP values of 22, 27, 32, and 37 to ensure a fair comparison and establish a target bitrate for the other algorithms. Therefore, the algorithms can be compared in four test points corresponding to these QP values.

We set the buffer capacity for the proposed RDOTP implementation to hold one second of video data at the target bitrate. To address inaccuracies in the R-D model that cause deviations between GA simulation results and real second-pass encoding results, a safety margin can be added to the

buffer size. In our simulations, the safety margin is 15% of the buffer size. The initial buffer occupancy was set to 0.65 times the buffer size [25]. These values were empirically derived through extensive testing to ensure strict compliance with the buffer constraint. Specifically, the 15% safety margin represents the worst-case scenario observed among the tested sequences and was required to cover the inaccuracy of the R-D model.

The VTM-RC algorithm used a default initial occupancy of 0.9 times the virtual buffer size. Extensive experiments were conducted, and the test video sequences were encoded at the four test points using the CQP, VTM-RC, FPI-D, Simul, and RDOTP algorithms.

The numerical experimental results at the test point of 27 are tabulated in Table III as sample results. This table details the resulting bitrate, the Peak Signal-to-Noise Ratio (PSNR) of the luminance component, the Structural Similarity Index Measure (SSIM), and the quality smoothness metrics. Furthermore, coding efficiency was assessed using the Bjøntegaard Delta (BD) metric, calculated across four test points for PSNR and SSIM. Tables IV and V summarize the comparative BD results, providing a comprehensive comparison of rate-distortion performance across all methods.

The bitrate, PSNR, and SSIM values in Table III indicate that the proposed RDOTP algorithm delivers superior objective quality. On average, it achieves performance nearly equal to that of the CQP method (PSNR: 41.99 vs. 41.90 dB, SSIM: 0.9748 vs. 0.9748). Compared with the VTM-RC algorithm, the proposed RDOTP algorithm yields significantly higher quality at a comparable bitrate (PSNR: 41.99 vs. 41.06 dB, SSIM: 0.9748 vs. 0.9708). As expected, compared with the FPI-D algorithm used during the first-pass encoding, the RDOTP algorithm achieves improved performance in the second pass (PSNR: 41.99 vs. 41.85, SSIM: 0.9748 vs. 0.9741). This improvement confirms the effectiveness of the optimization algorithm. This also demonstrates the high performance of our first-pass RC algorithm, which we tuned to achieve near-optimal results and minimize the inaccuracy effect of the R-D model used.

To evaluate the quality smoothness, which corresponds to the perceptual quality of encoded video, we defined three metrics based on MSE, including: Average of the absolute gradient of MSE (GD_{avg}) [32], variance of the absolute gradient of MSE (GD_{var}), and MSE variance (D_{var}). Smaller values of these metrics indicate lower MSE fluctuations, leading to higher perceptual quality in compressed video. The D_{var} metric reflects overall quality consistency by measuring the variance of the MSE across all individual frames. The GD_{avg} and GD_{var} metrics assess the temporal variations in video quality based on GOPs. To compute these metrics, the average MSE on all frames of each GOP, $D_{GOP}^{Avg,i}$

, is calculated, where i denotes the GOP index. Then, the absolute gradient of $D_{GOP}^{Avg,i}$ for all consecutive GOPs, GD_{GOP}^i , is extracted as:

$$GD_{GOP}^i = \left(\left| D_{GOP}^{Avg,i} - D_{GOP}^{Avg,i-1} \right| \right), \quad (27)$$

where computing the mean and variance of GD_{GOP}^i values over all GOPs yields the GD_{avg} and GD_{var} metrics. Resulted values of these quality smoothness metrics (GD_{avg} , GD_{var} , D_{var}) across the test sequences at the test point of 27, are reported in Table III. The results in this table confirm that the CQP method, a benchmark known for delivering stable and high visual quality, yields the lowest values for the quality fluctuation metrics, ($GD_{avg}=0.04$, $GD_{var}=0.20$, $D_{var}=1.06$), compared to other algorithms. This validates that these metrics are inversely proportional to the perceptual quality. According to the results, the proposed RDOTP algorithm achieves significantly higher perceptual quality ($GD_{avg}=0.13$, $GD_{var}=0.25$, $D_{var}=1.87$) than VTM-RC ($GD_{avg}=0.95$, $GD_{var}=0.64$, $D_{var}=6.79$) and the FPI-D ($GD_{avg}=0.64$, $GD_{var}=0.48$, and $D_{var}=3.99$) algorithms. Additionally, the results presented in Table III reveal strong consistency between the GA simulation results, Simul, and the real encoding results, RDOTP, in the second pass. These confirm the robustness and reliability of the proposed approach. The slight discrepancies observed are primarily due to inaccuracies in the R-D model during the second pass. However, it is noteworthy that the second-pass encoding consistently improves over the first-pass results, underscoring the effectiveness of GA-based optimization in the proposed RC algorithm.

The R-D performance was evaluated to further assess the proposed RDOTP algorithm against the CQP, VTM-RC, and FPI-D algorithms. Using the BD metrics computed on PSNR and SSIM values, the comparative results are presented in Tables IV and V, respectively. According to the average results in Table IV, the RDOTP algorithm demonstrated an R-D performance slightly better than CQP (BD-Rate: -2.36%, BD-PSNR: 0.08 dB) and significantly better than VTM-RC (BD-Rate: -27.37%, BD-PSNR: 1.36 dB). The results also show that compared to the first-pass, FPI-D, the R-D performance is improved in the second-pass, RDOTP (BD-Rate: -2.19%, BD-PSNR: 0.08 dB). This small gain proves that the FPI-D first-pass controller is near-optimal as intended. Also, this additional improvement achieved by the proposed GA-based framework demonstrates its ability to effectively exploit the remaining R-D optimization potential at the sequence level.

The average results presented in Table V show that the RDOTP algorithm demonstrated R-D performance close to

Table III. Experimental results of the CQP, VTM-RC, FPI-D, Simul, and RDOTP at QP of 27 on long test videos

Num.	Video Seq.	Method	Criteria						
			Bitrate (Mbps)	PSNR (dB)	SSIM	RD_{avg}^{norm}	GD_{avg}	GD_{var}	D_{var}
1	LV1	CQP	1801.6	38.74	0.9645	0.92	0.45	0.14	4.53
		VTM-RC	1826.1	38.51	0.9608	0.91	1.30	3.55	22.94
		FPI-D	1812.1	38.79	0.9634	1.00	1.04	2.28	16.35
		Simul	1819.9	-	-	0.94	0.83	1.11	11.89
		RDOTP	1824.2	38.91	0.9643	0.94	0.66	0.57	8.01
2	LV2	CQP	961.0	42.59	0.9831	0.94	0.16	0.02	0.25
		VTM-RC	969.1	41.44	0.9781	1.40	0.62	0.54	5.16
		FPI-D	950.4	42.50	0.9822	1.00	0.45	0.40	1.70
		Simul	970.4	-	-	0.94	0.34	0.27	1.26
		RDOTP	970.7	42.69	0.9829	0.92	0.18	0.02	0.61
3	LV3	CQP	701.8	43.37	0.9796	0.95	0.14	0.01	0.13
		VTM-RC	711.7	42.54	0.9768	1.39	0.42	0.27	1.33
		FPI-D	693.7	43.28	0.9791	1.00	0.32	0.21	0.82
		Simul	708.1	-	-	0.93	0.24	0.10	0.56
		RDOTP	705.4	43.44	0.9797	0.91	0.14	0.01	0.23
4	LV4	CQP	1581.0	42.23	0.9763	0.94	0.12	0.01	0.24
		VTM-RC	1589.2	41.12	0.9711	2.00	0.47	0.29	3.59
		FPI-D	1562.4	42.16	0.9756	1.00	0.35	0.22	0.81
		Simul	1597.3	-	-	0.95	0.26	0.14	0.62
		RDOTP	1597.9	42.29	0.9761	0.94	0.14	0.02	0.35
5	LV5	CQP	1232.6	42.58	0.9706	0.97	0.14	0.01	0.15
		VTM-RC	1242.3	41.70	0.9671	1.99	0.37	0.08	0.91
		FPI-D	1214.1	42.54	0.9704	1.00	0.22	0.07	0.27
		Simul	1244.1	-	-	0.95	0.17	0.03	0.21
		RDOTP	1243.1	42.64	0.9708	0.94	0.15	0.01	0.13
6	Average	CQP	1255.6	41.90	0.9748	0.94	0.04	0.20	1.06
		VTM-RC	1267.7	41.06	0.9708	1.54	0.95	0.64	6.79
		FPI-D	1246.5	41.85	0.9741	1.00	0.64	0.48	3.99
		Simul	1268.0	-	-	0.94	0.33	0.37	2.91
		RDOTP	1268.3	41.99	0.9748	0.93	0.13	0.25	1.87

that of CQP (BD-Rate: 0.5%, BD-SSIM: -0.0002) and was significantly better than VTM-RC (BD-Rate: -29.58%, BD-SSIM: 0.0084). The results also show that compared to the first-pass, FPI-D, the R-D performance is improved in the second-pass, RDOTP (BD-Rate: -3.36%, BD-SSIM: 0.0006). It is worth noting that the CQP is known as the best encoding method in terms of R-D performance.

The methods reviewed in Section II were identified based on their relevance to two-pass rate control, rather than their suitability as comparison baselines. Therefore, their direct quantitative comparison with the proposed algorithm is not straightforward. The methods in [29, 30, 32] were developed for the HEVC standard, making cross-standard quantitative comparison potentially misleading given the fundamental architectural differences between HEVC and H.266/VVC. Furthermore, although the method in [31] is VVC-oriented, it diverges significantly from the proposed framework regarding the underlying reference software, encoder configurations, evaluation metrics, and RC level. Consequently, a direct quantitative comparison would yield limited interpretability.

For further evaluation, the proposed RDOTP controller is compared with the two-pass RC approach in [31]. Although the two approaches target different operating scenarios and are evaluated under distinct experimental settings, both report coding gains relative to their corresponding CQP

anchors. Specifically, RC in [31] is designed for short-term bitrate control within the VVenC encoder, operates at the frame level with a GOP size of 32, and reports BD-Rate improvements using the XPSNR quality metric. Meanwhile, RDOTP targets long-term bitrate control within the VTM reference software, operates at the GOP level with a GOP size of 16, and evaluates coding efficiency in terms of PSNR-based BD-Rate. Under their respective evaluation conditions, the method in [31] achieves a 1.84% BD-Rate reduction relative to VVenC CQP, while RDOTP attains a 2.36% reduction relative to VTM CQP.

To assess the proposed method's performance in terms of the optimization problem objective, the normalized average R-D value, RD_{avg}^{norm} , is computed for each encoding method and reported in Table III. This involves computing the RD_{avg} , as defined in Equation (14), and normalizing it to the constant RD_{avg}^{PI} . According to the average results, the RDOTP provided the minimum value of RD_{avg}^{norm} , 0.93, and close to that of the CQP, 0.94. These values are much lower than those of VTM-RC, 1.54.

Generally, the objective of the proposed RDOTP algorithm is to optimize RD performance subject to a buffer constraint. Comparing it with the first-pass shows that the first-pass RC is already nearly optimal. However, the proposed method further reduces fluctuations in video

Table IV. Comparison results of the RDOTP controller versus CQP, VTM-RC, and FPI-D algorithms in terms of BD-Rate and BD-PSNR

No.	Video Sequence	RDOTP vs. CQP		RDOTP vs. VTM-RC		RDOTP vs. FPI-D	
		BD-Rate “%”	BD-PSNR “dB”	BD-Rate “%”	BD-PSNR “dB”	BD-Rate “%”	BD-PSNR “dB”
1	LV1	-3.57	0.14	-18.18	0.80	-2.13	0.08
2	LV2	-1.91	0.09	-26.77	1.79	-1.62	0.08
3	LV3	-1.71	0.07	-28.35	1.56	-2.26	0.09
4	LV4	-2.16	0.06	-29.98	1.47	-2.21	0.07
5	LV5	-2.46	0.05	-33.56	1.17	-2.74	0.06
Average		-2.36	0.08	-27.37	1.36	-2.19	0.08

Table V. Comparison results of the RDOTP controller versus CQP, VTM-RC, and FPI-D algorithms in terms of BD-Rate and BD-SSIM

No.	Video Sequence	RDOTP vs. CQP		RDOTP vs. VTM-RC		RDOTP vs. FPI-D	
		BD-Rate “%”	BD-SSIM	BD-Rate “%”	BD-SSIM	BD-Rate “%”	BD-SSIM
1	LV1	1.34	-0.0005	-22.84	0.0098	-4.15	0.0012
2	LV2	1.60	-0.0004	-29.68	0.0105	-2.89	0.0005
3	LV3	-1.03	0.0001	-27.67	0.0073	-3.15	0.0005
4	LV4	2.72	-0.0004	-33.71	0.0088	-3.18	0.0004
5	LV5	-2.12	0.0002	-33.99	0.0057	-3.45	0.0003
Average		0.50	-0.0002	-29.58	0.0084	-3.36	0.0006

quality, making it almost as stable as CQP. Importantly, unlike CQP, our approach controls the bitrate.

Fig. 5 plots the evolution RD_{avg}^{norm} computed by the GA for five video sequences for illustrative purposes. The y-axis and the x-axis represent the RD_{avg}^{norm} and the number of iterations, respectively. As shown in the figure, the normalized average R-D value derived by the GA steadily decreases as the number of iterations increases. This convergence trend indicates that the GA-based approach employed in the second pass effectively optimizes R-D performance, reducing the normalized average R-D from 1 to 0.94, on average, as observed in Table III.

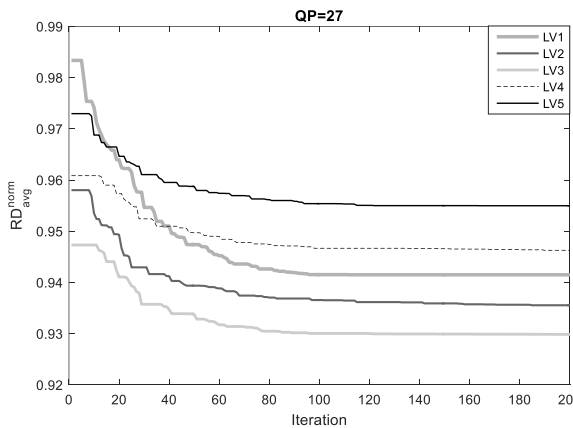
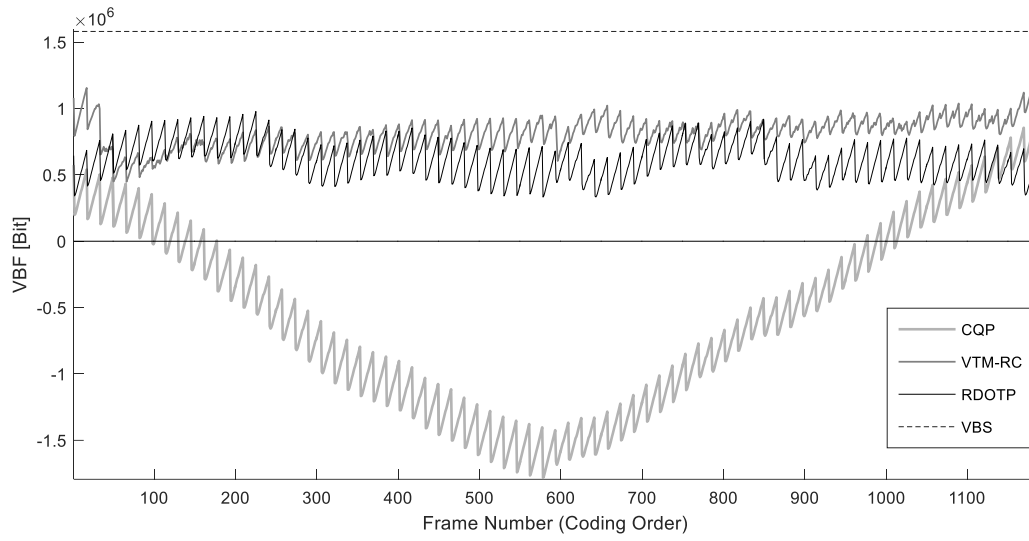


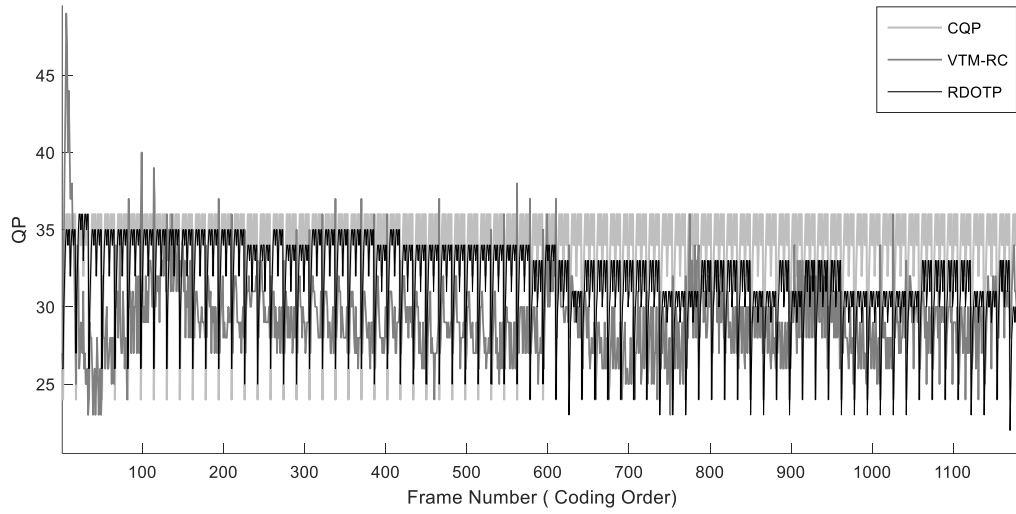
Fig. 5. The normalized average R-D values achieved during GA iterations for the five test sequences at the test point of 27

Fig. 6 presents some graphical results of encoding the LV4 test sequence as a sample. The figure depicts the buffer fullness, QP, and PSNR graphs for the compared algorithms in the a, b, and c subplots, respectively. These graphs are plotted in the encoding order. The dotted line indicates the buffer size in the buffer fullness graphs. According to the graphs, the CQP approach lacks bitrate and buffer control, while it provides a uniform PSNR pattern by using a fixed QP pattern for GOP frames. The VTM-RC controls the bitrate and buffer fullness at the expense of considerable fluctuations in QP and PSNR. In contrast, the proposed RDOTP effectively suppresses the undesirable fluctuations in QP and PSNR, thereby achieving higher perceptual quality than the VTM-RC.

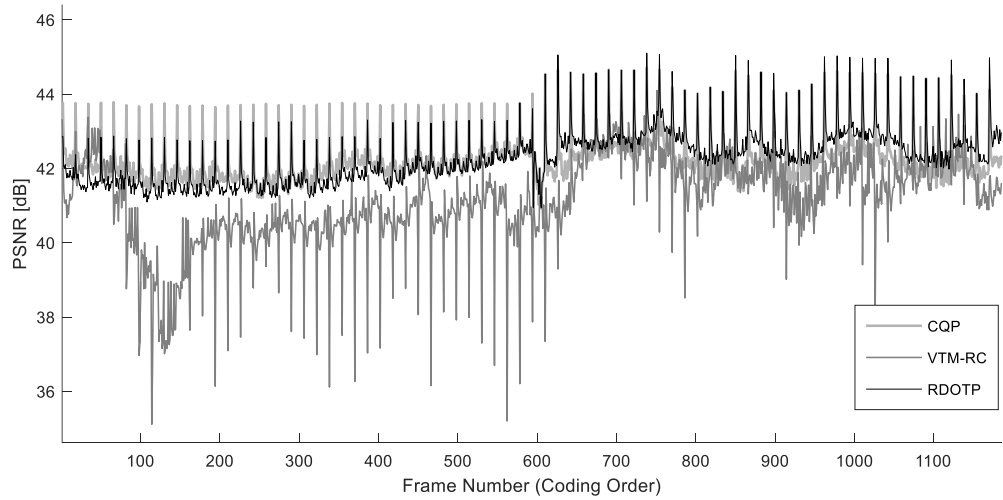
Hiding the effect of QP cascading from the LV4 encoding results for precise analysis, Fig. 7 plots the base QP graphs for the FPI-D and RDOTP algorithms, alongside the average GOP distortion (D_{avg}^{GOP}) for all compared algorithms, in a and b subplots, respectively. The comparison of the base QP curves reveals that RDOTP successfully surpasses the undesired QP variations of the sub-optimal first-pass encoding, FPI-D. This optimal QP selection in the second pass leads to a reduction in the fluctuation of the average GOP distortion, D_{avg}^{GOP} , ultimately contributing to a higher perceptual video quality. Furthermore, the RDOTP D_{avg}^{GOP} graph closely follows the graph of the CQP algorithm, which is known for its high perceptual quality. In contrast, VTM-



(a)



(b)



(c)

Fig. 6. The graphs of (a) the buffer occupancy, (b) QP, and (c) PSNR for LV4 sequence encoded by the CQP case, VTM-RC, and RDOTP algorithms at QP of 27

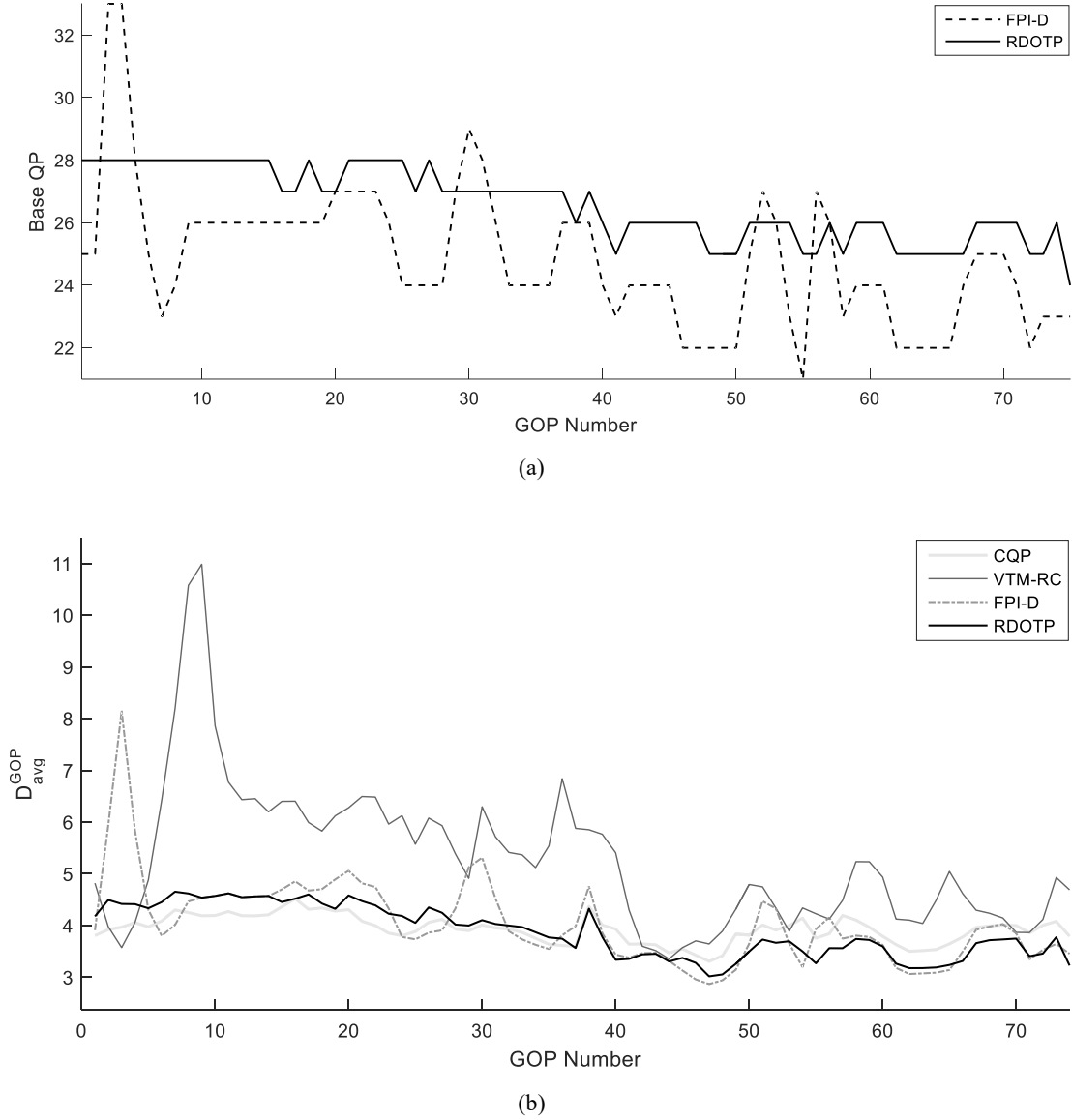


Fig. 7. The graphs of (a) the base QP encoded by the FPI-D, and RDOTP, and (b) the average distortion per GOP encoded by the CQP case, VTM-RC, FPI-D, and RDOTP algorithms for LV4 sequence at QP of 27

RC exhibits significant D_{Avg}^{GOP} fluctuations due to its frame-level operation and aggressive bitrate control, introducing noticeable variations in compressed video quality.

From a computational standpoint, the proposed framework introduces additional encoding complexity due to the optimization performed during the second pass. This additional workload is a natural consequence of the offline nature of two-pass rate control, which is designed for delay-insensitive applications like VoD delivery and streaming. In these cases, coding efficiency is typically prioritized over encoding speed. As a result, the extra computational cost is a practical trade-off for

improvements in R-D performance, better buffer management, and enhanced temporal quality stability.

V. Conclusions

A novel R-D-optimized rate-control algorithm tailored for VBR offline applications of the H.266/VVC standard is proposed in this paper. The proposed algorithm employs a two-pass GOP-level RC mechanism. During the first pass, the FPI-D controller estimates the GOP-level base QP by leveraging inter-GOP correlation and refining it based on bitrate and buffer constraints. Subsequently, in the second pass, the GA minimizes the sequence-level R-D objective function to optimize GOP-level QPs globally across the entire video sequence, ensuring adherence to buffer

constraints. The experimental results on the VTM-15.1 reference software indicate that the proposed algorithm achieves superior performance to existing approaches for the GA optimization R-D objective, yielding substantial bitrate savings and quality improvements while adhering to the buffering constraint. The results also confirm that the proposed RDOTP algorithm outperforms the compared algorithms in the Bjontegaard Delta-PSNR and Delta-SSIM. According to the results, the RDOTP algorithm minimizes QP fluctuations, leading to stable, high perceptual quality in compressed video. The encoding simulation results of the optimization algorithm and the actual encoding results in the second pass match very closely. This proves that the results of the proposed algorithm are indeed optimal. For future work, the framework could be extended to a multi-objective optimization approach that explicitly accounts for both R-D performance and quality fluctuations, potentially enhancing the effectiveness of rate control in practical applications.

REFERENCES

- [1] W. Hamidouche *et al.*, "Versatile video coding standard: A review from coding tools to consumers deployment," *IEEE Consumer Electronics Magazine*, vol. 11, no. 5, pp. 10-24, 2022. <https://doi.org/10.1109/MCE.2022.3144545>
- [2] B. Bross *et al.*, "Overview of the versatile video coding (VVC) standard and its applications," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 31, no. 10, pp. 3736-3764, 2021. <https://doi.org/10.1109/TCSVT.2021.3101953>
- [3] Y. Y. Adrian Browne, Seung Hwan Kim, "Algorithm description for Versatile Video Coding and Test Model 21 (VTM21)," *JVET-AD2002-v1*, 2023.
- [4] X. Wei, M. Zhou, H. Wang, H. Yang, L. Chen, and S. Kwong, "Recent Advances in Rate Control: From Optimisation to Implementation and Beyond," *IEEE Transactions on Circuits and Systems for Video Technology*, 2023. <https://doi.org/10.1109/TCSVT.2023.3287561>
- [5] H. Zeng, J. Xu, S. He, Z. Deng, and C. Shi, "Rate Control Technology for Next Generation Video Coding Overview and Future Perspective," *Electronics*, vol. 11, no. 23, p. 4052, 2022. <https://doi.org/10.3390/electronics11234052>
- [6] M. Wang, J. Zhang, L. Huang, and J. Xiong, "Machine learning-based rate distortion modeling for VVC/H.266 intra-frame," in *2021 IEEE International Conference on Multimedia and Expo (ICME)*, 2021: IEEE, pp. 1-6. <https://doi.org/10.1109/ICME51207.2021.9428378>
- [7] Y. Mao, M. Wang, Z. Ni, S. Wang, and S. Kwong, "Neural network based rate control for versatile video coding," *IEEE Transactions on Circuits and Systems for Video Technology*, 2023. <https://doi.org/10.1109/TCSVT.2023.3262303>
- [8] Z. Zhao, X. He, S. Xiong, L. He, H. Chen, and R. E. Sheriff, "A High-Performance Rate Control Algorithm in Versatile Video Coding Based on Spatial and Temporal Feature Complexity," *IEEE Transactions on Broadcasting*, 2023. <https://doi.org/10.1109/TBC.2023.3268946>
- [9] F. Brand, C. Herglotz, and A. Kaup, "A low-parametric model for bit-rate estimation of VVC residual coding," in *ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2022: IEEE, pp. 1860-1864. <https://doi.org/10.1109/ICASSP43922.2022.9747694>
- [10] M. Zhou, X. Wei, W. Jia, and S. Kwong, "Joint decision tree and visual feature rate control optimization for VVC UHD coding," *IEEE Transactions on Image Processing*, vol. 32, pp. 219-234, 2022. <https://doi.org/10.1109/TIP.2022.3224876>
- [11] Y. Chen, M. Wang, S. Wang, Z. Ni, and S. Kwong, "A ctu-level screen content rate control for low-delay versatile video coding," *IEEE Transactions on Circuits and Systems for Video Technology*, 2023. <https://doi.org/10.1109/TCSVT.2023.3243225>
- [12] J. Lin, A. Huang, K. Zhang, X. Wang, and T. Zhao, "\$\lambda\$-domain VVC Rate Control Based on Game Theory," *arXiv preprint arXiv:2205.03595*, 2022. <https://doi.org/10.48550/arXiv.2205.03595>
- [13] J. Lin, A. Huang, T. Zhao, X. Wang, and S. Kwong, "\$\lambda\$-Domain VVC Rate Control Based on Nash Equilibrium," *IEEE Transactions on Circuits and Systems for Video Technology*, 2022. <https://doi.org/10.1109/TCSVT.2022.3231335>
- [14] F. Liu and Z. Chen, "Multi-objective optimization of quality in VVC rate control for low-delay video coding," *IEEE Transactions on Image Processing*, vol. 30, pp. 4706-4718, 2021. <https://doi.org/10.1109/TIP.2021.3072225>
- [15] Y. Li, Z. Liu, Z. Chen, and S. Liu, "Rate control for versatile video coding," in *2020 IEEE International Conference on Image Processing (ICIP)*, 2020: IEEE, pp. 1176-1180. <https://doi.org/10.1109/ICIP40778.2020.9191125>
- [16] F. Raufmehrer, M. R. Salehi, and E. Abiri, "A frame-level MLP-based bit-rate controller for real-time video transmission using VVC standard," *Journal of Real-Time Image Processing*, vol. 18, pp. 751-763, 2021. <https://doi.org/10.1007/s11554-020-01018-2>
- [17] H. Liu, S. Zhu, and B. Zeng, "Inter-frame dependency-based rate control for vvc low-delay coding," *IEEE Signal Processing Letters*, vol. 29, pp. 2727-2731, 2022. <https://doi.org/10.1109/LSP.2023.3234774>
- [18] Y. Sha and J. Yang, "Rate Control Optimization Algorithm Based on R-\$\lambda\$ Model in H.266/VVC," *Journal of Research in Science and Engineering (JRSE)*, vol. 4, no. 2, 2022, doi: 10.53469/jrse.2022.04(02).06.
- [19] Y. Mao, M. Wang, S. Wang, and S. Kwong, "High efficiency rate control for versatile video coding based on composite Cauchy distribution," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 32, no. 4, pp. 2371-2384, 2021. <https://doi.org/10.1109/TCSVT.2021.3093315>
- [20] Y. Chen, S. Kwong, M. Zhou, S. Wang, G. Zhu, and Y. Wang, "Intra frame rate control for versatile video coding with quadratic rate-distortion modelling," in *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing*

- (ICASSP), 2020: IEEE, pp. 4422-4426. <https://doi.org/10.1109/ICASSP40776.2020.9054633>
- [21] F. Raufmehr, M. R. Salehi, and E. Abiri, "A neural network-based video bit-rate control algorithm for variable bit-rate applications of versatile video coding standard," *Signal Processing: Image Communication*, vol. 96, p. 116317, 2021. <https://doi.org/10.1016/j.image.2021.116317>
- [22] F. Raufmehr, M. R. Salehi, and E. Abiri, "Overcoming the practical restrictions in H. 266/VVC-based video communication systems by a PI bit rate controller," *Multimedia Systems*, vol. 28, no. 5, pp. 1723-1739, 2022. <https://doi.org/10.1007/s00530-022-00942-6>
- [23] F. Raufmehr, M. R. Salehi, and E. Abiri, "A neuro-fuzzy QP estimation approach for H. 266/VVC-based live video broadcasting systems," *Multimedia Tools and Applications*, vol. 83, no. 19, pp. 56423-56443, 2024. <https://doi.org/10.1007/s11042-023-17795-4>
- [24] F. Raufmehr and M. R. Salehi, "Video Rate Controller Development Through Neuro-Fuzzy Quantization Parameter Modifiers," *Journal of Signal Processing Systems*, vol. 95, no. 6, pp. 751-764, 2023. <https://doi.org/10.1007/s11265-023-01877-5>
- [25] A. Nakhaei, M. Rezaei, and M. Kazeminia, "Fuzzy proportional-integral-derivative rate controller for variable bitrate applications of versatile video coding standard," *Journal of Electronic Imaging*, vol. 33, no. 6, pp. 063040-063040, 2024. <https://doi.org/10.1117/1.JEI.33.6.063040>
- [26] G. He, K. Xu, C. Wu, Z. Ma, X. Wen, and M. Sun, "Hybrid video coding scheme based on VVC and spatio-temporal attention convolution neural network," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2022, pp. 1791-1794. <https://doi.org/10.1109/CVPRW56347.2022.00193>
- [27] C. R. Helmrich *et al.*, "A scene change and noise aware rate control method for vvenc, an open vvc encoder implementation," in *2022 Picture Coding Symposium (PCS)*, 2022: IEEE, pp. 241-245. <https://doi.org/10.1109/PCS56426.2022.10018041>
- [28] C. R. Helmrich, A. Henkel, T. Hinz, A. Wieckowski, B. Bross, and D. Marpe, "Finalization of VVenC's Screen Content Detector and Two-Pass Rate Control Using Pre-Filtering Statistics," in *2023 IEEE International Conference on Image Processing (ICIP)*, 2023: IEEE, pp. 1160-1164. <https://doi.org/10.1109/ICIP49359.2023.10223193>
- [29] S. Wang, A. Rehman, K. Zeng, and Z. Wang, "SSIM-inspired two-pass rate control for high efficiency video coding," in *2015 IEEE 17th International Workshop on Multimedia Signal Processing (MMSP)*, 2015: IEEE, pp. 1-5. <https://doi.org/10.1109/MMSP.2015.7340805>
- [30] S. Wang, A. Rehman, K. Zeng, J. Wang, and Z. Wang, "SSIM-motivated two-pass VBR coding for HEVC," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 27, no. 10, pp. 2189-2203, 2016. <https://doi.org/10.1109/TCSVT.2016.2580398>
- [31] C. R. Helmrich, I. Zupancic, J. Brandenburg, V. George, A. Wieckowski, and B. Bross, "Visually optimized two-pass rate control for video coding using the low-complexity XPSNR model," in *2021 International Conference on Visual Communications and Image Processing (VCIP)*, 2021: IEEE, pp. 1-5. <https://doi.org/10.1109/VCIP53242.2021.9675364>
- [32] A. Nakhaei and M. Rezaei, "Scene-level two-pass video rate controller for H. 265/HEVC standard," *Multimedia Tools and Applications*, vol. 80, no. 5, pp. 7023-7038, 2021. <https://doi.org/10.1007/s11042-020-09710-y>
- [33] G. J. Sullivan, J.-R. Ohm, W.-J. Han, and T. Wiegand, "Overview of the high efficiency video coding (HEVC) standard," *IEEE Transactions on circuits and systems for video technology*, vol. 22, no. 12, pp. 1649-1668, 2012. <https://doi.org/10.1109/tcsvt.2012.2221191>
- [34] M. Mitchell, *An introduction to genetic algorithms*. MIT press, 1998. <https://doi.org/10.7551/mitpress/3927.001.0001>
- [35] *Algorithm description for Versatile Video Coding and Test Model 15 (VTM15)*, JVET-X2002-v1, J. C. Adrian Browne, Yan Ye, Seung Hwan Kim, 2021.
- [36] F. Bossen, J. Boyce, K. Suehring, X. Li, and V. Seregin, "VTM common test conditions and software reference configurations for SDR video," in "Joint Video Experts Team (JVET) of ITU-T SG 16 WP 3 and ISO/IEC JTC 1/SC 29," Document JVET-S2011, 19th Meeting, 2020.
- [37] A. Mercat, M. Viitanen, and J. Vanne, "UVG dataset: 50/120fps 4K sequences for video codec analysis and development," in *Proceedings of the 11th ACM Multimedia Systems Conference (MMSys '20)*, Istanbul, Turkey, 2020: Association for Computing Machinery (ACM), pp. 297-302, doi: 10.1145/3339825.3394937. [Online]. Available: <https://ultravideo.fi/dataset.html>



Arshnoos Nakhaei received the B.S. degree in communications engineering from, Sistan and Baluchestan University, zahedan, Iran, in 2015, and also M.Sc. degree in communications systems engineering at Sistan and Baluchestan University, Iran, in 2018. He is currently pursuing the Ph.D. degree in communications systems engineering. His research interests include multimedia signal processing and communications.



Mehdi Rezaei (M'04) received his B.Sc. and M.Sc. in electronics engineering from Amir Kabir University and Tarbiat Modares University, Iran, in 1992 and 1996, and his Ph.D. in signal processing from Tampere University of Technology, Finland, in 2008. His research interests include multimedia signal processing and communications. He has collaborated with Nokia, holding several patents and papers. He is currently an Associate Professor in the Communications Engineering Department at the University of Sistan and Baluchestan.



Mahdi Kazeminia received a B.Sc., an M.Sc., and his Ph.D. in telecommunication engineering from the University of Sistan and Baluchestan, Iran, Zahedan in 2010, 2012, and 2019, respectively. From 2017 to 2018, he was a visiting researcher at the University of Padova, Padova, Italy. He is an assistant professor in the Department of Electronics at Velayat University, Iranshahr, Iran.

His research interests include resource allocation optimization, IoT networks, and D2D communication.