Biologically-Inspired Optimal Video Streaming over Unpredictable Wireless Channel

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Abstract

Recently there has been an alarming increase in demand for wireless video streaming and the need to provide the required quality of service (QoS) to support video applications is very crucial. It is obvious that supporting multimedia applications and services over wireless is very challenging task due to network heterogeneity and different QoS requirements. This requires low complexity and highly efficient optimization scheme to cope with the unpredictable channel condition. This paper is aimed at developing a biologically-inspired scheme using particle swarm optimization (PSO) to achieve optimal video streaming. The optimal parameters configuration selected provide the best settings to enhance the video streaming quality over wireless LAN. The scenario has been simulated in NS-2 environment, it clearly shows that the video quality has been improve by selecting best configuration to ultimately support video application. The PSO-based approach outperforms other techniques used to compare the performance of the develop scheme in terms of perceived video quality by more than 0.5dB. The experimental simulation has been used to verify the efficiency and potential application of the PSO in wireless multimedia networks.

Keywords: *Particle swarm optimization, Quality of service, Optimal configuration, Swarm-based algorithm, Channel condition*

1. Introduction

Optimization is becoming an increasingly important tool in order to achieve optimal solution and effective resource allocation especially in time-varying transmission environment. This is primarily due to dramatic need for efficient and economical design solution, and allocating limited resources [1]. With rapid growth of optimization techniques in recent years, more complicated communication and networking problems can be solved with relative ease and sophistication. More importantly, advancement in computing has contributed tremendously toward achieving more remarkable results with high precision and accuracy. Also, the geometric increase in size and complexity of problems as a result of technological advancement has necessitated the need for more systematic and efficient approach. In a nut shell, optimization is extremely important tool used to determine the best solution to a given problem within a set of constraints.

Wireless multimedia communication has witnessed an exponential growth due to high demand; and hence it requires efficient strategies to ultimately support multimedia applications over erroneous channel. The alarming increase in utilization and number of users with different QoS requirements increase the computational complexity and time. For delay sensitive application, it is very challenging to achieve the necessary QoS required to ultimately support wireless multimedia communication [2, 3, 4, 5, 23]. Bio-inspired algorithms have developed mainly based on the successful evolutionary behavior of natural system - which naturally mimic nature and adapts dynamically with the environment. These algorithms can be used in solving complex problems with high precision and sophistication. In order to perform more complex computations within shortest possible time, there is need for highly efficient and sophisticated optimization technique which converges very fast and simple to be implemented. Particle swarm optimization (PSO) [6, 7, 8, 9, 10, 21, 22] has been extremely important tool which dramatically reduce the processing time and complexity as well. This is primarily due to its convergence and searching capability. The aforementioned characteristics of PSO when fully exploited can play more significant role in minimizing the time required to make critical decision. PSO is a well-known optimization technique which is based on social and cognitive behavior.

The unpredictable nature of wireless environment makes it difficult to manage the resources available within the network more effectively. Hence, there tremendous need for optimization to effectively manage the network resources properly due increasing number of wireless station which have detrimental impact on the network performance [11]. It is a known fact that multimedia applications are very much sensitive to delay and hence high priority is needed to be given to such application in order to be transported over unpredicted channel condition.

In order to support wireless multimedia communication, more than one QoS parameters should be considered to enhance the performance of the network. Hence, multi-criteria decision approach is needed and PSO is used to properly manage the conflicting multi-objective functions. Real-time optimization problems are multi-objective in nature and therefore multi-objective PSO can simultaneously and efficiently determines the best optimal solution within the packet deadline [12, 13, 14]. The ability to meet up with packet deadline is very important in delay sensitive application where any delay can seriously affect the multimedia content.

The remainder of this paper is organized as follows. Section II mainly focuses on the general overview of PSO. Section III introduces our proposed strategy using particle swarm optimization. Simulations results are presented in Section IV. Finally, conclusions are enumerated in Section V.

2. Particle Swarm Optimization

Swarm intelligence has been used extensively in solving optimization problems and it primarily uses biologically inspired approach to select best optimal solution. Its principle is purely based on simulating the movement of flock of birds or school of fish. It has been extremely important tool and can potentially tackle complex optimization problems. Many different swarm optimization techniques exist today and this primarily includes Ant, Bee, Glow warm etc. In fact, PSO has been very promising due to its fast convergence and simplicity. This can be applicable in supporting delay sensitive applications which require highly efficient and low computation complexity. It is very obvious that in order to enhance the performance of wireless multimedia applications, many parameters and factors should be considered. Hence, multi-objective optimization PSO can eventually solve variety of multi-objective problems to achieve optimal performance. More importantly, multi-objective PSO can effectively search and determine the set of optimal solutions simultaneously. The wireless channel characteristic can be represented by highly non-linear objective and constraint in order to genuinely consider its impact on the transmitted data or information.

Particle swarm optimization mainly used stochastic and population based optimization approach to mimic the natural phenomenon. It primarily produces a set of solution and further modified as the process continues. This has been very efficient and powerful tool for searching the optimal solution to a given particular problem. In general, PSO normally used to have one objective function but due to confliction between the functions require an efficient strategy to determine the best possible solution. It has been a major challenge because by increasing one of the functions can have detrimental impact on the other function. Therefore, this subsequently leads to development of multi-objective optimization to properly handle the situation. Problems dealing with multiple objective function can be solve using multi-objective PSO with relative ease and high searching capability for optimum solution [15][16]. Due to aforementioned reasons, multi-objective PSO can be used in wireless network to ultimately support multimedia applications and services.

It is important to note that PSO is based on velocity and position equations. The velocity and position of a particle at time t can be represented by v(t) and x(t). It is used in selecting the best position and fitness. For a particle with n dimension can be represented by vector $\boldsymbol{X} = (x_1, x_2 \dots \dots \dots x_n)$. The position of the particcles at time t can be mathematically expressed as $P = (p_1, p_2 \dots \dots \dots p_n)$ while the corresponding velocity of the particles is represented as $\boldsymbol{V} = (v_1, v_2 \dots \dots \dots v_n)$. The velocity and position of the particle at time t+1 can be determined using equation (1) and (2)

$$v(t+1) = \begin{cases} \omega v(t) + c_1\left(P_l + x(t)\right) \\ \quad +c_2\left(P_g + x(t)\right) \end{cases} \tag{1}$$

$$x(t+1) = x(t) + v(t+1) \tag{2}$$

The velocity equation basically describes the velocity of the particles at time t+1. v(t) keeps track of the particle flight direction and it prevents the particle from sudden change in direction. $c_1\left(P_l + x(t)\right)$ normally measures the performance of the particle relative to the past performance. In a nutshell, it draws the particles to their best known position. $c_2\left(P_g + xt\right.$ measures the performance of particle relative to the neighbours. Generally, it serves as standard in which individuals want to reach. Both the cognitive and social components depend greatly on c_1 and c_2 respectively.

The global best (P_g) determines the best possible solution for the entire neighborhood for each particle in the entire swarm. It is just a typical star topology in which the social component of the particle velocity update depends on the information obtained from all the particles in the swarm [17]. In star structure, the particles are interconnected and hence they can communicate with one another more efficiently and effectively. All the particles tend towards the best solution found in the swarm. The global best used star structure which converges faster, but can be trapped in local minima. The best possible position is determined by P_g. After the velocity is determined, the position is then computed using the x(t+1). It is very important to note that this will determine best possible position and velocity discovered by any particle at time (t+1).

However, it is very important to note that meeting up with the delay constraint in wireless multimedia network is a major issue of concern. Multi-objective cross layer optimizer using PSO can potentially select the optimal configuration within the time deadline. In the next section, the multi-objective decision criterion will be elaborated.

3. Optimal Video Streaming Using PSO-Based Approach

Generally, optimization problems which have more than one objective function termed as multi-objective optimization. It is absolutely possible that the objective functions conflict with one another while optimizing such a problem [18][19]. Multi-objective optimization has different possible solution to particular problem. In this particular case, the multi-objective optimization primarily consists of objective function, constraint and optimal solution. The main optimization task is achieved through multi-objective optimization which is primarily based on the concept of particle swarm optimization. The equation (1) and (2) describes the velocity and position of the particle at any particular time. More importantly, the PSO capability depends greatly on the aforementioned functions. At any particular time, the values for these functions are computed and best possible value is selected. Also, it is very much necessary to include the constraint in order to set boundary for the search space.

In fact, wireless environment require multi-objective optimization due to multiple objective functions describing various parameters of the network. The minimization problem can be represented mathematically as

$$\begin{aligned} &\textit{Minimize} \quad f(x) = (f(x_1), f(x_2), \ldots, f(x_n)) \\ &\text{Subject to} \quad x \in X \end{aligned} \tag{3}$$

Let us assumed that $f: R^n \rightarrow R$ and hence $x \in R^n$ can be determine if the condition $f(x) \leq f(\boldsymbol{x}), \forall x \epsilon R^n$ has been satisfied.

3.1 Problem Formulation

The problem can be represented as $G = (N, L)$, where N denotes the set of nodes and L is the set of communication link connecting the nodes together. It has been assumed that S is the sets of video source through which nodes stream the video content and L(s) is the link used by the source s. For any source to stream the video content, the packets firstly queued Q in buffer before they are served. The queue size changes randomly and it can be represented as set, where $Q = \{q_1, \ldots \ldots q_n\}$. The delay anticipated after the source placed request for the video content is termed as D, where $t = \{t_1, \ldots \ldots t_n\}$.

The objective functions are selected to provide the necessary QoS support for multimedia application over wireless network. The optimal video quality problem primarily determine the best parameter settings for minimum queue size and delay at particular time, and subsequently assign how the policy to use in transmitting the packet. It is aimed at setting the configurations which yields optimum performance at relatively low queue size and delay.

The joint sets of optimal solutions of the optimization problem can be represented mathematically in matrix form by

$$\begin{bmatrix} \varphi_1 \\ \cdot \\ \varphi_n \end{bmatrix} = \begin{bmatrix} Q_1 & D_1 \\ . & . \\ Q_n & D_n \end{bmatrix} \tag{4}$$

φ represents the optimal solution and n is the total number of solutions obtained. At each particular time, sets of optimal solutions are obtained and the best minimum among all solutions is selected to achieve optimal in video quality. It is based on the minimum value of φ selected, the number of packets to be transmitted is determined. This is mainly to avoid congestion within the network by adapting to the network condition. For each of the value selected, it has to conform to the maximum delay limit and it serves as constraint to optimization problem.

$$\boldsymbol{Q_i} = \frac{1}{N}\left(\sum_{i=1}^{n} q_i\right) \tag{5}$$

$$\boldsymbol{D_i} = \frac{1}{N}\left(\sum_{i=1}^{n} t_i\right) \tag{6}$$

The queue size and delay objective function are minimize subject to the delay constraint as in equation (8). The joint optimal video streaming quality φ_{opt} can be achieve by finding the minimum values for the queue, and delay at a particular time. The objective function is given as $f(Q,D) = \alpha.f(q) + (1-\alpha).f(t)$ which is a combination of the queue size and delay. The summation of $\alpha\ and\ (1-\alpha)$ should be equal to zero. The time required to serve each depends on the queue size.

Minimize: $\varphi_{opt} = argmin\ f(Q,D)$

Subject to: (7)

$0 \le t \le \mathbf{T}$ (8)

The above parameters are computed within the time delay limit t which should be less than the overall packet deadline T for the video application. It is very clearly that the algorithm shows more remarkable results by converging below the packet deadlines which indicated that the algorithm can be used for delay sensitive applications.

As can be seen from equation (9), it has been assumed that $f(Q,D)$ is the function representing the objective function with n different solutions of Q and D. This can be expressed in matrix form by

$$f(Q,D) = \begin{bmatrix} f(Q_1, D_1) \\ . \\ f(Q_n, D_n) \end{bmatrix} \tag{9}$$

Also, the constraints K for each of the above function can be represented in matrix form as shown in equation (10)

$$K(Q,D) = \begin{bmatrix} K(Q_1, D_1) \\ . \\ K(Q_n, D_n) \end{bmatrix} \tag{10}$$

The matrix $K(Q,D)$ describes the constraints which must be satisfied before achieving optimal solution without loss of generality. n is the number of constraints related to the above functions in equation (9).

Analytically, the objective function can be solved using partial differential equation as shown in equation (11). For instance, the gradient of the continuous differential equation f(Q_i, D_i) representing the problem can be determine by finding the second derivative at the value of $Q_i\ and\ D_i$ which satisfy the delay constraint. This can be represented mathematically as shown in equation (7)

$$\nabla \mathrm{f}(Q_i, D_i) = \begin{bmatrix} \frac{\partial f(Q_1, D_1)}{\partial q} & \frac{\partial f(Q_1, D_1)}{\partial t} \\ \cdot & \cdot \\ \frac{\partial f(Q_n, D_n)}{\partial q} & \frac{\partial f(Q_n, D_n)}{\partial t} \end{bmatrix} \tag{11}$$

By taking the second partial derivative of hessian matrix in equation (11) will eventually yields equation (12).

$$\nabla^2 \mathrm{f}(Q_i, D_i) = \begin{bmatrix} \frac{\partial^2 f(Q_1, D_1)}{\partial q^2} & \frac{\partial^2 f(Q_1, D_1)}{\partial t^2} \\ \cdot & \cdot \\ \frac{\partial^2 f(Q_n, D_n)}{\partial q^2} & \frac{\partial^2 f(Q_n, D_n)}{\partial t^2} \end{bmatrix} \tag{12}$$

3.2 PSO Parameters

In order to achieve optimal performance, a series of tests have been conducted to verify the convergence capability of the PSO-based algorithm by adjusting different parameters. It is very necessary to conduct thorough test of the optimization technique due to the wireless video streaming application requirement in which the scheme will be used. Obviously, it is of paramount importance to meet up with packet deadline when dealing with delay sensitive application such as video.

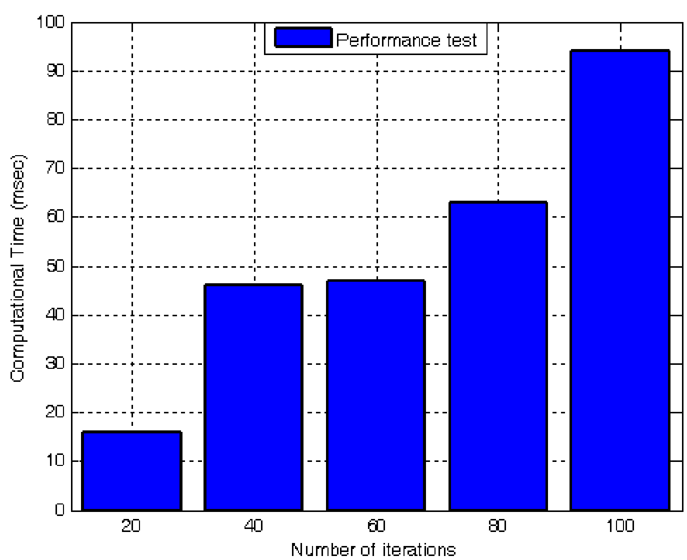

Figure 1. Effect of Number of Iteration on Computational Time

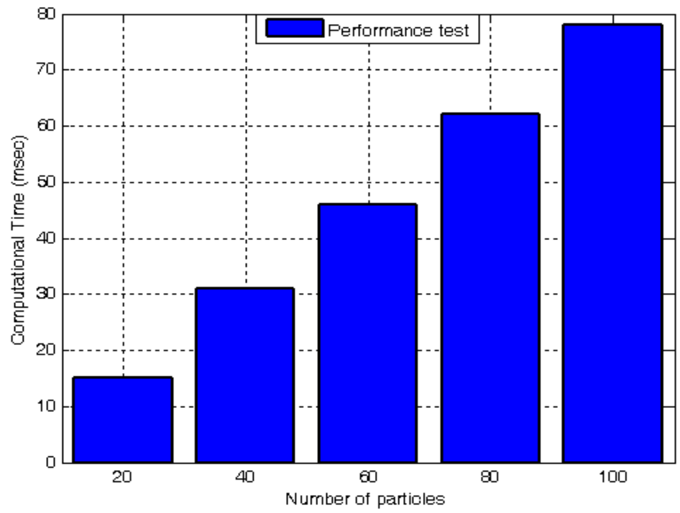

Figure 2. Effect of Number of Particles on Computational Time

As can be seen from Figures 1 and 2, the number of iterations and particles needed to meet with the video application requirement are experimentally determined. The problem of selecting the number of iteration need to be resolved due to the fact that setting it to a large value will results in unnecessary additional computational time. However, setting the iteration to small value will result in premature convergence which should be avoided in order to achieve optimal performance. Since the number of function target for this application has been restricted to four objective functions, the number of iteration was varied for different values and corresponding computational time under each scenario is determined. Based on the experiments, the number of iteration and particles are selected as 30 to suit the deadline for video streaming application over wireless. The number of iteration and particles used for the implementation PSO-based scheme is strategically selected based on the experiment conducted.

The biologically inspired algorithm for optimal video streaming application can be summarized as follows

Algorithm: PSO-Based algorithm for optimal video streaming quality

Objective function: **min** $f(Q, D)$
Initialize swarm with random positions and velocities of n particles

for loop over all n particles

Compute the values of $\mathbf{Q_i}$, and $\mathbf{D_i}$ at time t
Generate new velocity
Calculate new position based on the new velocity

// Evaluate objective function
Check delay constraints if less than packet deadline;
Compute the fitness of the particle based on $f(Q, D) = \alpha. f(q) + (1 - \alpha). f(t)$

```
    Select local best;
    Select global best;

    if current fitness of particle is less than previous and global, replace the previous
      Update particles velocities and positions
   end
      Increase the loop counter, t + 1
end  // once stopping condition has been reached；
```

Output $\boldsymbol{\varphi}_{\mathbf{opt}} = \text{argmin } f(Q, D)$

4. Simulation Results

In this section, the simulation results for PSO-based optimal streaming scheme is presented. The optimizer parameters have been set based on the particle swarm to suit the QoS requirement for video application. The maximum number of iterations and inertia weight were set to 30 and 0.5 respectively within which the optimal solution should determine or terminated. The cognitive c_1 and social c_2 constants have been set to 1. The delay constraint is checked before evaluating the fitness function for each objective function. Both local and global best are determined and subsequently the position and velocity of the particles are updated. If the condition for termination has been reached, the current best optimal parameter configurations are selected. When the termination condition has not been reached, the loop counter is compared with the number of particles. The process is repeated until the termination condition is reached.

The simulation has been conducted using NS-2 simulator [20] based on the settings in Table 1 and 2. The code for the PSO-based algorithm is integrated into NS-2 environment in order to select the best solution to optimization problem. We simulated the scenario using QCIF (176X144) video samples which are encoded at 30fps. The video model used for the experiment consists of an I-frame and 14 P-frame. All of the two QCIF video samples are encoded with the same group structure for the video streaming application. Also, the pattern of the encoded frames is IPPPP.... In between each I-frames, there are 14 P-frames. Hall and News video samples were used in the simulation to effectively analyze the performance of the scheme. The proposed scheme is compared with static and rate distortion optimization schemes to verify the performance of the developed approach.

Table 1. PSO Parameter Settings

Parameters	Value
Number of particles	30
Number of iteration	30
Learning factors c_1 & c_2	1
Inertia weight	0.5

Table 2. Network Settings

Parameters	Value
Propagation model	Shadowing
PhyType	Phy/WirelessPhy/802_11
MacType	Mac/802_11
freq_	2.4 GHz
Data rate	1 - 11 Mbps
CSThresh_	1-13
RXThresh_	1.10765e-11
Video Samples (QCIF)	Hall, News
Number of frames	300

Based on the experimental results obtained, it is very obvious that the scheme can be applicable for wireless video streaming application which eventually requires reliable and robust mechanism to meet up with the delay constraint. Simulations show that the proposed technique increases the media quality. The scheme has improved video streaming quality caused mainly due to time varying channel condition, heterogeneity and congestion.

The video quality of each video frame is measured using peak signal to noise ratio (PSNR). The mean square error (MSE) for each frame is converted to PSNR by mapping the 8-bits original signal. The actual difference or loss in video quality is computed mathematically using equation (13).

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \tag{13}$$

Where MSE can be computed using the formula in equation (14)

$$MSE = \frac{1}{NM}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}\left(\vartheta_S(i,j) - \vartheta_D(i,j)\right)^2 \tag{14}$$

ϑ_S(i,j) represent the original source frame and ϑ_D(i,j) is the reconstructed frame at the destination which contain NxM pixels.

In order to investigate and analyze the performance of the developed approach, rate distortion optimization (RDO) and static schemes have been used in making comparison with the proposed scheme. RDO tremendously assists in analyzing and estimating RD functions in visual coding and communication. The efficiency of coding can be improved by ensuring optimum bit allocation. The quantization setting of the encoder is controlled based on the channelcondition and available storage capacity.

Table 3. Video Quality Comparison

	Video Quality (dB)	
Technique	**Hall**	**News**
Static	31.29	31.87
RDO	31.88	32.79
PSO-Based	33.87	33.29

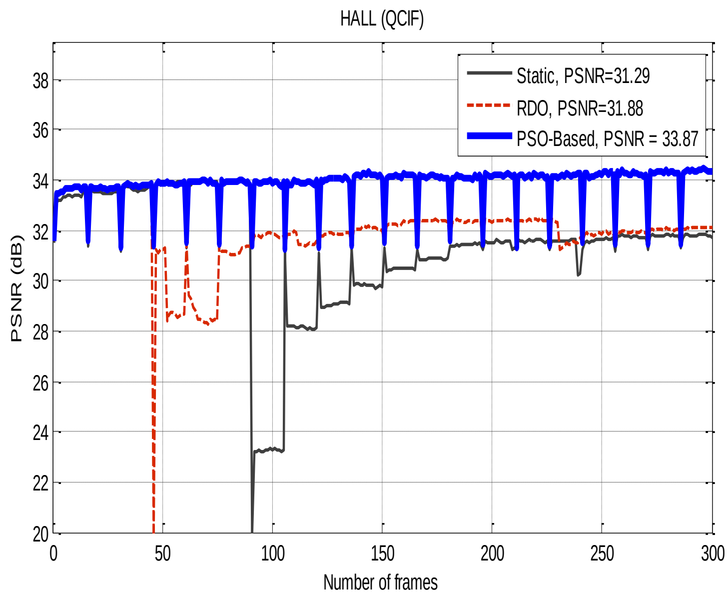

Figure 3. Comparison of PSO-Based Optimal Video Streaming Scheme with Other Strategies

HALL (176X144 @ 30fps)

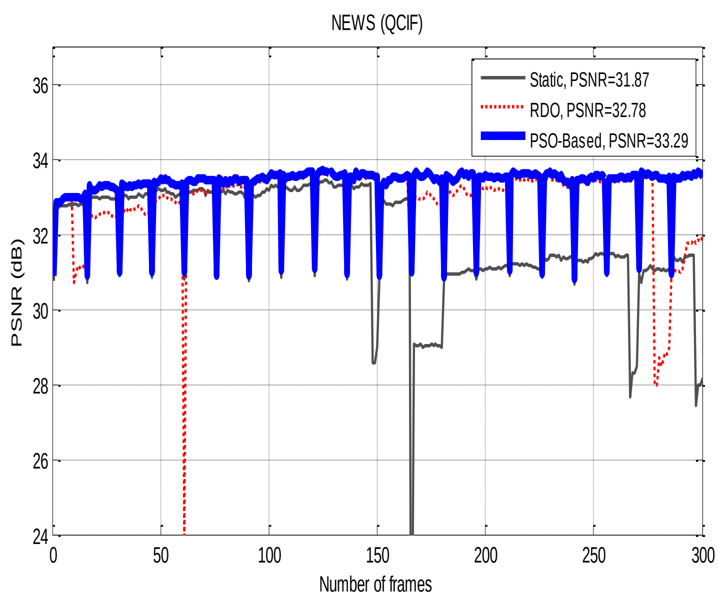

Figure 4. Comparison of PSO-Based Optimal Video Streaming Scheme with Other Strategies

NEWS (176X144 @ 30fps)

From Figures 3 and 4, it can be seen that the video quality has been reasonably maintained in both hall and news video samples. This is primarily due to adaptive capability of the scheme to time varying environment. The proposed scheme uses queue and delay statistic in real-time and subsequently adjusts the transmission rate in order to meet up with the constraint of the video content. When compared to RDO, the PSO-based has improved the video quality of hall and news video samples by 1.99 and 0.5 dB respectively. Moreover, the PSO-based scheme outperforms the non-optimized or static approach in terms of video quality by 2.58dB and 1.42dB for hall and news video samples respectively. Also, it can be notice that as the complexity of the video samples increases, the perceived video quality decreases. The PSO-Based scheme features such as self-configurable, self-adaptable and self-autonomous makes the scheme more robust and resilient to unpredictable wireless channel variation

6. Conclusion

In this paper, we proposed an efficient strategy to select best possible optimal solution in multi-criteria decision problem in order to ultimately support delay sensitive application. It fundamentally presents a new approach to reduce the complexity of cross layer and at the same time achieved better video quality. More importantly, the PSO-Based approach has shown more promising result for achieving high convergence which meets up with the time constraint for video application. The biologically inspired approach using PSO is very effective, simple, flexible and high searching capability which can potentially be used in making critical decision in error prone transmission environment. Our future work will adapts this technique in developing multi-objective cross layer optimization for wireless video streaming application and services.

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