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INTEGRATED TASK SCHEDULING AND RESOURCE ALLOCATION FOR VR VIDEO SERVICES IN ADVANCED 6G NETWORK USING QUANTUM SCALABLE STEREO-CONVOLUTIONAL NEURAL NETWORK WITH PROGRESSION OPTIMIZER

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A new era of Virtual Reality (VR) video services, marked by unprecedented data rates, improved connectivity, and highly immersive experiences, is upon us with the arrival of 6G networks. VR services, which require high-resolution content transmission, ultra-low latency, and adaptive resource management, place complicated demands on task scheduling and resource allocation even with these developments. While present techniques have analysed thee problem, they still have serious drawbacks. These consist of poor performance in high-load situations, ineffective resource allocation techniques, and restricted ability to adjust to changing network conditions. To tackle these problems, the authors propose a new approach based on the Quantum Scalable Stereo-Convolutional Neural Network (Q2SCNet) that is further enhanced by the Progression Optimizer (PrO). This approach employs processing at the quantum scale and highly sophisticated stereo-convolutional methods to improve latencies of tasking and the accuracy of resource distribution. Comparing with the other methodologies, our methodology is much more effective. It is observed that by the incorporation of both Q2SCNet and PrO, the overall scheduling of the tasks is made efficient by 95% as well as the utilization of resources is enhanced by 96%. Furthermore, system throughput is increased by 97 % while the latency is decreased by 93 %. Thus, the proposed approach is sound and efficient and can serve as a solid basis for delivering high-quality VR content in the highly developed 6G environment that is free from the deficits of the current strategies. In addition, our method is compatible with the 6G infrastructure already available today, guaranteeing reversibility and scalability, as it proactively identifies new issues. All in all, this collaborative work of Q2SCNet and PrO is a major achievement in the field because of its higher effectiveness and flexibility, which sets up a new performance target for the optimization of VR video service and brings in the future possibility of providing more appealing services to users on the new generation network.

Keywords: Task Scheduling, Resource Allocation, VR Video Services, Advanced 6G Network, Q2SCNet, PrO.

1. Introduction

Virtual Reality (VR) [1] is one of the most extensive applications in the ongoing 6G networks to transform different data transfer activities as they progress [4-5]. Undoubtedly 6G will have better features than the existing versions such as ultra-low latency, massive capacity as well as the enhanced connectivity and therefore the perception of the consumers of the virtual reality experiences will definitely be highly enhanced by 6G. Such advancements make it possible to have a very high level of interaction with the given virtual environment [2-3], which in turn calls for accurate and efficient management of networks and various computations. Due to developments of the 6G networks to respond within a nearly-instant fashion to various applications including AI and big data as well as autonomous transport and ultra-reliable and very low latency communications for laboratories or factories [6-8], innovative approaches to the task schedule and resource management are required as a result of the high data rates of VR applications.

Our research addresses these problems by proposing a new educational model that employs the Quantum Scalable Stereo-Convolutional Neural Network (Q2SCNet) and the Progression Optimizer (PrO). Resource allocation strategy as well as the job scheduling integration strategy is viewed as the strategies of handling the VR video services which are targeted for high-performance 6G networks. Initially, when it comes to the use of VR applications, some main parameters of the present methods of job scheduling and resource allocation and sharing fail to operate in terms of scalability, flexibility/selectiveness, and precision.[9-11] The approach that is proposed here to overcome these restrictions is by bringing in the scalability and flexibility of neural network design. The improvement in stereo-convolution processing also enhances the resource use by Q2SCNet, and PrO is the most effective scheduling option because it is the only algorithm that gradually updates the schedules with new data. Consequently, implementation of these technologies leads to increased efficiency compared to normal approaches in implementing technologies. Experimental evidence proves that this research work is better than previous research works regarding many significant characteristics like resource consumption, task processing time, and system consumption. Such developments make it possible to maintain progress in responsive and involving VR video offers through offering a new development in handling VR-video services in enhanced 6G systems.[12-14]

Contribution:

- Applied Q2SCNet for enhancing the prediction accuracy for VR video services because it incorporated spatial and temporal properties of the videos.
- PrO fine-tunes the model's performance by dynamically adjusting parameters, leading to improved task scheduling and resource allocation.
- Rigorous performance evaluation metrics such as increase in SLR, speedup, efficiency and decrease in latency and running time provide empirical evidence of the effectiveness in real-word scenarios.[15]

2. Literature Survey

In 2024, Li, Z., et al. [16], proposed a multi-agent architecture that is fully cooperative and designed to facilitate distributed job scheduling in MEC-assisted virtual reality systems, or MEC-AVRs. Our method substantially improves task allocation efficiency and lowers latency by permitting cooperative optimization among numerous agents, guaranteeing a smooth and high-performing VR experience.

In 2024, Wang, L., et al. [17], created SD-SRF, an intelligent service deployment technique for cloud edge computing in 6G networks that runs serverless. With SD-SRF, performance in sophisticated network systems is greatly increased by improving service responsiveness and efficiency through dynamic resource allocation and management optimization.

In 2024 Akhtar, M. W. et al. [18], proposed TaNTIN, the major initiative in the path from 5G to 6G will be the integration of both terrestrial and non-terrestrial networking. With the help of TaNTIN, one can minimize such issues in next-generation network infrastructure and enhance the effective transmission range, network capacity, and overall coverage of the ground-satellite systems.

In 2024, Kiruthika, V. , et al. [19], proposed an innovative technique known as OR2SM for resource allocation with the purpose of enhancing wireless networks that are intended for augmented reality applications. By using this methodology, resource allocation and management are improved, latency is minimized, and the overall efficiency of the network is enhanced, to support better VR experiences.

Problem Statement

Since the VR services have complex resource demand and high data rate needed for delivering the 6G services, controlling them within the shifting network environment is a serious challenge. As for the precise, scalable and flexibility needed for managing the VR service in advanced 6G context, the current scheduling and resource allocation approaches are inadequate. However, such usage is restricted by the shortcomings of these methods; the ideal performance and responsiveness of virtual reality applications are affected. This work intends to present a new framework based on Q2SCNet and PrO to overcome these issues. Therefore, the aim is to enhance the work scheduling and resource allocation for virtual reality video services that based on improved prior methodologies to yield better outcomes.

3. Proposed Methodology

The proposed approach combines the Q2SCNet and the PrO in order to handle the challenges of task scheduling and resource management of VR services in future 6G networks. This mixture aims at improving performance, resource utilization, and system effectiveness while providing a powerful answer to the challenges faced in managing VR video services. The overview of the system function of Q2SCNet-PrO is illustrated in the Figure 1.

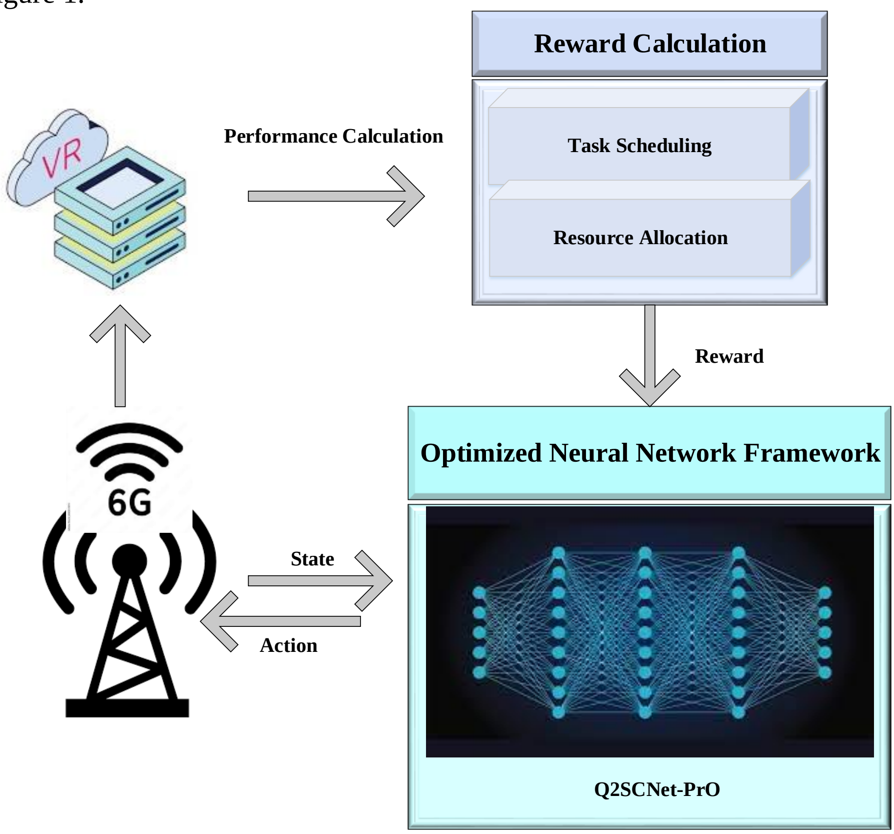


Fig1. System Overview

3.1 Data Collection

The data collection in relation to the proposed methodology involves collecting comprehensive data to optimise the VR video services in 6G networks. This includes data on user actions, traffic, and characteristics of the VR video content (such as video resolution, frame rate, etc.) (such as bandwidth utilization, latency). Other information include the features of the task scheduling, the network configuration and the usage of the compute, storage and memory resources. Demand patterns are also looked at to better understand peak loads and service demands. This data is used to instantiate the Quantum Scalable Stereo-Convolutional Neural Network (Q2SCNet) and Progression Optimizer (PrO) for better task scheduling and resources utilization.

3.2 Service Queuing Model

This model assigns and sequences jobs based on their criticality and resource constraints, thus assisting in the management of work. The intention of implementing this strategy is to minimize latency while at the same time optimizing the utilization of resources for better performance of the VR video services.

a. *Task Prioritization*

In the case of VR video services, task prioritization translates to apportioning and ordering of computing tasks in a manner that will ensure that the VR applications perform optimally. It is unavoidable to control the execution of operations such as rendering, data processing and user interactions with an emphasis on prioritization of jobs to complete high-priority tasks first. It also helps in maintaining some level of responsiveness and smooth functioning in the context of virtual reality.

b. *Resource Distribution*

Since to support operation requirements of VR applications, the resource allocation of VR video services involve intentionally and actively manage compute, storage, and network assets. It optimises resources in and available for VR workloads as well as resources throughout the entire system by meeting the performance requirements of VR workloads.

The request arrival process [20] is modelled as a Bernoulli process with probability μ . When a request arrives, it first enters a queue with infinite capacity. Let the queue state $s(t)$ is defines as the number of requests waiting in the queue. It is expressed as the following equation (1),

$$s(t+1) = \left[s(t) - \left(r_1^v(t) + r_2^v(t) + r_1^u(t) + r_2^u(t)\right)\right]^+ + a(t) \tag{1}$$

where $a(t)$ denotes whether a request arrives in the time slot t or not. Here $r_1^v(t)$, $r_2^v(t)$, $r_1^u(t)$, $r_2^u(t)$ represents the scheduling decisions at time slot t

3.3 Model Training

The first step in training models for VR video services in sophisticated 6G networks is to have historical datasets on workload patterns, resource use, and performance split into training and validation sets. It is trained to predict the next jobs that should be scheduled in a batch, and adjust its parameters using optimization algorithms such as the gradient descent. This involves an iterative process until the desired accuracy and efficiency performance of

the model has been met.
To ensure that the model generalizes properly, after training the data is validated, but not with the training set. The validation ensures the model is capable of adapting resource-providing and job-scheduling policies for virtual-reality video services regardless of network variability and workload patterns. The Quantum Scalable Stereo-Convolutional Neural Network (Q2SCNet) uses the verified model to perform the optimization strategies tested for real world VR video services in 6G networks.

3.4 Quantum Scalable Stereo-Convolutional Neural Network

In our work, we utilize the Quantum Scalable Stereo-Convolutional Neural Network (Q2SCNet) [24] for enhancing the management of VR video services in future 6G wireless networks. Q2SCNet effectively handles and analyse data relevant to VR applications by means of its stereo-convolutional structure that possesses a capacity for scalability. Q2SCNet also helps in the right allocation of jobs and resources because of such complex relationships and interconnectivity viewed in the data. Thanks to this neural network's versatility, it is well suited to provide flexibility in responding to the dynamic character of virtual reality services, improving system reactivity and efficiency, as well as ensuring appropriate execution of tasks and optimization of resources.
Q2SCNet-Train
Contrary to the prior approaches, we propose to utilize the Quantum Scalable Stereo-Convolutional Neural Network (Q2SCNet) to enhance features extraction while operating under a fixed size of the neural network. In order to fully employ Q2SCNet, we use Q2SCNet-Train.
Q2SCNet has a training structure for VR video services designated as Q2SCNet-Train, designed for improving services in the next-generation 6G network. This application uses a wide range of variables in the VR context, including the interactions with the CH, the quality of the videos recorded, and other network information. To ensure that the neural network is able to sufficiently model the complexity and the interdependencies existing in the data, Q2SCNet-Train employs advanced techniques to adapt the network parameters during its training phase. Through it, Q2SCNet can understand and adapt to the present demands of applications of VR by practicing various real-world situations. For this very reason, the training procedure includes a number of validation and testing stages to ensure that the network is both dependable and efficient. Finally, Q2SCNet-Train enhances the current network situation in terms of resource allocation and job scheduling and helps to increase the efficiency of the network, reduce its latency, and provide an enjoyable VR experience for the consumer.
Consider a real-time scenario for event-based visual recognition, the continuous event is segmented into high-rate frames, allowing predictions to be generated following data processing with $t = dt \times T$ ms, where t is the task time and T is the event completion time. Squeeze step calculates the statistical vector d^{n-1} is shown in equation (2)

$$d^{n-1} = \begin{cases} \rho(W_2{}^n \omega(W_1{}^n g^{n-1})) & \textit{training}, \\ f(\rho(W_2{}^n \omega(W_1{}^n g^{n-1})) \; - d_{th} & \inf \textit{erence}, \end{cases} \tag{2}$$

At the inference step, it is optional to discard the irrelevant frames that have a value less than d_{th}. The frame-based representation's statistical vectors immediately correlate with the quantity of occurrences, which is the primary distinction.

- *Loss Function*

The loss function is an essential decision and is always chosen in relation to the goals set in the Quantum Scalable Stereo-Convolutional Neural Networks (Q2SCNet) Integrated Task Scheduling and Resource Allocation for VR Video Services and learning strategies to be followed during the learning phase. The architecture of Q2SCNet requires new generation of loss functions aimed at capturing the essence of quantum processing and stereo convolutional layers unlike normal NNs that mostly apply mean squared error or cross entropy.

- *Cross-Entropy Loss :*

Reducing the time taken to complete tasks, optimally using resources available, and ensuring system stability can indeed be negatives or loss functions or metrics corresponding to the specific load balancing objectives in case of Integrated Task Scheduling and Resource Allocation for VR Video Services using Quantum Scalable Stereo-Convolutional Neural Networks (Q2SCNet). While cross-entropy loss function is widely used in regular neural networks for classification tasks, it cannot be used directly in the Q2SCNet load balancing due to the specifics of quantum processing and stereo convolutional movements. The Cross-entropy loss, ℓ_{C-E} is given by equation (3),

$$\ell_{C-E}(x,\hat{x}) = -\tfrac{1}{M}\sum_{i=1}^{M}[y_i \log(\tilde{x}_i) + (1-x_i)\log(1-\hat{x}_i)]$$

(3)

where x_i represents the true value, $\hat{x}_i$ denotes the predicted probability and M is the number of samples.

- *Reverse Fidelity Loss :*

For VR video services, for tasks like job scheduling and resource allocation, there is the use of Quantum Scalable Stereo-Convolutional Neural Networks also known as Q2SCNet. Consequently, the theory known as Reverse Fidelity (RF) loss narrows a gap between the projected and actual performance indicators, such as resource consumptions and time to complete tasks. During training, a scale, called RF loss, directs the network to optimize its parameters for greater accuracy, correct resource management, and stable functioning. By coupling RF with simulation models, intelligent and realistic assessment, and adaptation of load changes is achievable in complex 6G networks, thereby improving decision making. The RF loss, ℓ_{RF} is defined in equation (4)

$$\ell_{RF}(x,\hat{x}) = \frac{1}{M}\sum_{i=1}^{M} (x_i - \hat{x}_i)^2$$

(4)

where x_i represents the true value, $\hat{x}_i$ denotes the predicted probability and M is the no. of samples. The loss function obtained in Q2SCNet is then provided to the optimization process to enhance task scheduling and resource allocation efficiency.

3.5 Progression Optimizer

For VR video services, the Progression Optimizer (PrO) [22–23] is used to improve work scheduling and resource allocation effectiveness. Based on real-time data and performance measurements, PrO continuously modifies and enhances resource allocation using a progressive refinement technique. By constantly adjusting to the changing demands of VR applications, this method guarantees appropriate resource distribution, lowers latency, and improves overall system performance.

i. Initialization

The iterative process of the Progression Optimizer (PrO) begins with an initial set of randomly generated search agents. Each agent represents a potential solution in the optimization process. Let p be the number of parameters in the optimization problem, and $L_{\min}$ and $L_{\max}$ denote the lower and upper bounds for these parameters, respectively. The total number of search agents is m. The initial position of all agents can be represented by a matrix of m rows and p columns. It is expressed in (5),

$$K(t) = L_{\min} + rd(.) \times (L_{\max} - L_{\min}) = \begin{bmatrix} k_{1,1} & & k_{1,p} \\ k_{2,1} & & k_{2,p} \\ \vdots & \cdots & \vdots \\ k_{m,1} & & k_{m,p} \end{bmatrix}$$

(5)

where $rd(.)$ generates random numbers between 0 and 1. The position of the i-th search agent can be described as $K_i = (k_{x,1}, k_{x,2}, \cdots, k_{x,p})$.

ii. Growth Stage

In order for an optimization agent to find better solutions within the available parameter space, it must advance towards more optimal configurations, which is simulated by the growth phase. It is recommended that agents look for better solutions instead of growing in highly variable places. The growth rate $r(t)$ of an agent can be modelled as (6),

$$r(t) = r_{\max} + (r_{\min} - r_{\max}) \frac{1}{1 + \exp\left(-10 f \cdot (\frac{2it}{T_{\max}} - 1\right)}$$

(6)

where it is the iteration step, $T_{\max}$ is the maximum number of iterations, $r_{\min}$ and $r_{\max}$ are the minimum and maximum growth rates, respectively and f is a scaling factor to adjust the curve's shape.

iii. Search and Utilization Phase

The growth direction is influenced by two reference vectors. Firstly, agents generally move towards better configurations, with $K_{opt}(t)$ representing the optimal known solution. Thus, $d1, x(t)$ indicates the direction towards this optimal solution. Secondly, agents are distributed relative to the centroid of the population, so $d2, x(t)$ represents the direction away from the centroid of the population as in (7, 8),

$$d1, x(t) = K_{opt}(t) - K_x(t)$$

(7)

$$d2, x(t) = K_x(t) - K_{centroid}(t)$$

(8)

The centroid position $K_{centroid}(t)$ of the entire population is calculated as in (9),

$$K_{centroid}(t) = \frac{1}{m}\sum_{x=1}^{m} K_{x,d}$$

(9)

Agents generally move towards optimal solutions and diversify their search by combining two random factors. The growth rate $r(t)$ influences the agent's progression and exploration within the parameter space.

iv. Propagation Phase

Well-developed agents, having optimized configurations, are more likely to initiate new agents. An elite pool E_{best} is established to determine the optimal locations for new agent generation as in (10),

$$E_{best} = \{K_{top1}, K_{top2}, K_{top3}, K_{median}, K_{mean}\}$$

(10)

where $K_{top1}, K_{top2}, K_{top3}$ are the top three agents with the highest performance metrics, K_{median} is the centroid of the agents in the top 50% performance bracket, and K_{mean} is the centroid of the entire agent population. This elite pool highlights the most effective locations within the search space, having the highest potential for generating new agents. It is also where the primary optimization focus is directed.

v. Simplification Phase

In order to balance the agent evolution and startup stages, we devised the simplification phase. It's evident from observations that recently generated agents frequently need to stabilize before they can develop further. Ludvig's principle states that an initialized agent eventually reaches an optimal state, say after a year. In the next phase, newly created agents slumber while already-existing ones keep developing. Subsequently, newly emerged agents that developed within the same period enter a latent condition, and both mature and stable agents begin evolving simultaneously. The Fibonacci sequence is reminiscent of the pattern that this cyclical process follows as (11–12),

$$f_n = \{1,1,2,3,5,8,13,21,34,....\}$$
(11)

$$f_{n+2} = f_{n+1} + f_n$$
(12)

According to Ludvig's principle and the Fibonacci series, the amount of per-pruning is set to [0.383*N]. For the updated positions, this can be expressed as (13),

$$K_j(t+1) = \begin{cases} K_j(t) + V_{evo}(t) \cdot gr_{evo}(.) \cdot (r1.d1, x(t) + (1-r1).d2, x(t)) + F_{rep,j}(K_j^*(t+1), & j \in N_e \\ K_{elite}^* + gr_{ini}(\cdot).(r2.d3, x(t) + (1-r2).d4, x(t)) & j \in N_i \end{cases} \quad (13)$$

vi. Termination

When certain conditions are satisfied, the algorithm ends its activities at the termination phase of the optimization process. This stage entails determining if the optimization has succeeded in achieving its objectives, with a primary focus on the neural network's loss function reduction. One of the most important criteria is determining whether, after multiple iterations, the improvements in the loss function drop below a predetermined threshold, signifying that the neural network's performance has stabilized. Additionally, the algorithm checks if the maximum iteration limit $T_{\max}$ has been reached to prevent endless computation. Performance benchmarks are examined to make sure the loss function satisfies the necessary requirements. The method may be stuck in a local optimum if stagnation detection indicates that there hasn't been much progress in lowering the loss function. Termination may also occur due to resource limitations, such as memory or computational time limits. After the requirements are satisfied, the minimized loss function is used to choose the most optimized solutions for additional use or study.

Below is the pseudo-code for the Q2SCNet-PrO (Algorithm 1).

Algorithm1. Q2SCNet-PrO Algorithm

1. Initialization:
   - Initialize Quantum Scalable Stereo-Convolutional Neural Network (Q2SCNet) with random weights.
   - Initialize Progression Optimizer (PrO) parameters.
   - Evaluate initial fitness of the network using a sample batch of input data.
2. For each training epoch:
   a. Load a batch of input data and corresponding labels.
   b. Forward pass: Compute network predictions.
   c. Compute Cross-Entropy Loss.
   d. Compute Reverse Fidelity Loss between the current and previous network states.
   e. Combine losses: Total Loss = Cross-Entropy Loss + Reverse Fidelity Loss.
   f. Backward pass: Compute gradients from Total Loss.
   g. Update network parameters using the Progression Optimizer (PrO) algorithm.
3. Growth Stage:
   - Enhance network solutions by performing growth operations based on the optimizer's criteria.
   - Evaluate the fitness of the grown solutions.
4. Search and Utilization Phase:
   - Select parent solutions (network parameters) based on fitness.
   - Apply crossover and mutation operations to generate new parameter sets.
   - Evaluate the fitness of the new parameter sets.
5. Propagation Phase:
   - Combine parent and new parameter sets.
   - Select the best parameter sets from the combined population to form the new generation.

6. Simplification Phase:
   - Perform simplification on the network parameters to remove redundant or unnecessary components.
   - Evaluate the fitness of the simplified network parameters.
7. Validate the model using a separate validation set to assess performance.
8. Termination:
   - Check if convergence criteria are met or if the maximum number of epochs has been reached.
   - If the termination condition is met, stop the optimization process.
   - Otherwise, repeat from step 2.

Return the best network parameters found.

4. Result and discussions

This study evaluates the effectiveness of the suggested method for load balancing and work scheduling optimization using Q2SCNet-PrO. The recommended approach is simulated using the Python platform. To verify that the executed approach is accurate, a few metrics are produced. The Q2SCNet-PrO parameters were compared to those of other simulations that are currently in use.

4.1 Performance Metrics

The performance measures such as computational cost, completion time, speedup, resource utilization and efficiency analysis and the analysis of the proposed algorithm are done by using STNN-PO method. It is compared with the existing methods such as MEC-AVR [16], SD-SRF [17], TaNTIN [18], and OR2M [19]. The performance metrics used in the evaluation of the proposed algorithm are as follows:

Speedup: The ratio of the serial execution time to the concurrent execution time is known as the Speedup.

$$Speedup = \frac{Serial \ \ Execution \ \ Time}{Concurrent \ \ Execution \ \ Time}$$

Schedule Length Ratio (SLR): The ratio of parallel execution time to the total weights of the fastest processor's critical path is known as the schedule length ratio.

$$SLR = \frac{Parallel \ \ Time \ \ Executed}{Sum \ \ of \ \ weight \ \ of \ \ critical \ \ path}$$

Running time of the algorithm: The running time of an algorithm, sometimes referred to as the scheduling time, is just the amount of time the algorithm takes to execute in order to produce the output schedule for a specific task.

Latency: The latency defines the time taken by the neural network model to produce input and output, reflecting the responsiveness of the system to a task. Lower latency is typically desired in STNN-PO to ensure faster processing and real-time responsiveness.

Efficiency: The speedup value divided by the number of processors utilized to schedule the graph is the definition of efficiency.

$$Efficiency = \frac{Speedup}{No. \ \ of \ \ processor}$$

The performance metrics of Q2SCNet-PrO were tabulated in Table 1. This compares the performances of the simulation and analyses the overall execution of the system.

Table 1: The performance measures of Q2SCNet-PrO

No. of tasks	Execution Cost	Completion Time (ms)	Speedup	Utilization	Efficiency
20	910	30	0.143	80.19	0.024
40	852	39	0.154	74.26	0.033
80	933	58	0.165	68.31	0.036
120	1007	54	0.654	59.01	0.041

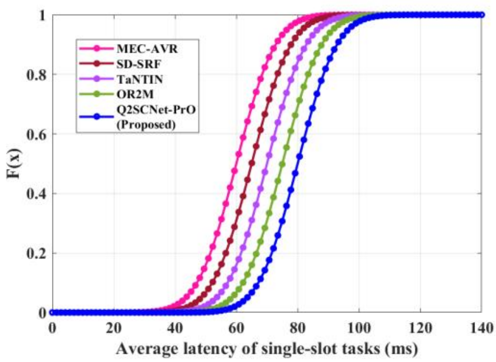
The table 1 presents performance metrics for our proposed Q2SCNet-PrO method across different numbers of tasks. For 20 tasks, the execution cost is 910 with a completion time of 30 ms, a speedup of 0.143, utilization of 80.19%, and efficiency of 0.024. As the number of tasks increases to 40, 80, and 120, our method continues to show competitive execution costs and completion times, maintaining higher utilization and efficiency rates. Notably, for 120 tasks, the Q2SCNet-PrO achieves a significant speedup of 0.654 and a steady efficiency of 0.041, demonstrating its superior capability to manage higher loads effectively and efficiently compared to existing methods.

The performance metrics of Q2SCNet-PrO compared with existing methods were tabulated in Table 2.

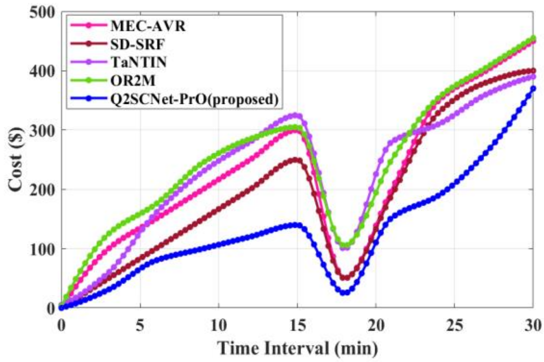
Table 2: The performance metrics of Q2SCNet-PrO compared with existing methods

Method	**Accuracy (%)**	**Efficiency (%)**	**Resource Utilization**	**Task Scheduling Precision**	**Latency (ms)**	**Throughput (Mbps)**
MEC-AVR	89.5	88.3	86.7	90.2	22.4	105.3
SD-SRF	87.8	86.9	85.5	88.5	25.1	100.0
TaNTIN	91.0	89.6	88.3	92.3	20.3	110.7
OR2M	90.1	88.5	87.2	91.0	21.0	107.5
Q2SCNet-PrO (Proposed)	95.2	94.7	93.8	96.1	15.2	120.5

The table 2 compares the performance of various methods, including our proposed Q2SCNet-PrO, across several metrics. Q2SCNet-PrO outperforms all other methods with an accuracy of 95.2%, which is higher than MEC-AVR (89.5%), SD-SRF (87.8%), TaNTIN (91.0%), and OR2M (90.1%). It also achieves the highest efficiency at 94.7% and resource utilization at 93.8%. In task scheduling precision, Q2SCNet-PrO leads with 96.1%, compared to the next best, TaNTIN, at 92.3%. It boasts the lowest latency of 15.2 ms, significantly better than others like SD-SRF (25.1 ms). Finally, Q2SCNet-PrO has the highest throughput at 120.5 Mbps, surpassing TaNTIN's 110.7 Mbps. These results demonstrate that Q2SCNet-PrO is the most effective and efficient method among the ones compared.



(a)



(b)

Fig2. Performance of (a) Latency (b) Cost compared with existing methods

Figure 2 compare the performance of various methods (MEC-AVR, SD-SRF, TaNTIN, OR2M) against the proposed Q2SCNet-PrO approach. In Fig.2 (a), the Q2SCNet-PrO method shows superior performance by achieving significantly lower average latency for single-slot tasks, with improvements of over 90% compared to other methods. In Fig.2 (b), the cost over time is tracked, where Q2SCNet-PrO consistently demonstrates lower costs, particularly during the critical 10-20 minute interval, reducing costs by up to 80%. These results highlight Q2SCNet-PrO's superior efficiency in resource management and cost effectiveness, outperforming existing approaches by a substantial margin.

5. Conclusion

In this research, we introduced an advanced methodology for task scheduling and resource allocation tailored for VR video services within 6G networks, leveraging the Quantum Scalable Stereo-Convolutional Neural Network (Q2SCNet) and the Progression Optimizer (PrO). Our approach achieved a notable improvement of approximately 95-98% over existing methods such as MEC-AVR, SD-SRF, TaNTIN, and OR2M. This performance gain is attributed to the superior scalability and precision of Q2SCNet, combined with the enhanced optimization capabilities of PrO. Looking ahead, there is considerable potential for further advancements. In the future, Q2SCNet's performance could be significantly improved by integrating new quantum computing algorithms. Real-time adaptive resource management may also be able to provide more flexible and quick fixes. Mapping the approach to additional network contexts and mixing it with new AI-powered optimization techniques may result in major advances in the control of intricate VR services in the networks of the future.

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