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Cross-Layer Design for Combining Adaptive Modulation and Coding with DMMPP Queuing for Wireless Networks

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Abstract: Resource management and Quality of Service (QoS) are seen as key concerns for many applications in 5G networks since they support millions of linked devices. When sharing information over error-prone wireless networks, these resource management strategies are necessary to fulfill multimedia applications with a minimum throughput guarantee, low error probability, and high tolerated delay. One of the most complex traffic management strategies that provide fair QoS for channel users is queuing. According to queuing research, Adaptive Modulation and Coding (AMC) functions well when the buffer does not overflow. The typical AMC must be revised together with the queuing process when there is an overflow to lower the Packet Error Rate (PER) and Packet Dropping Probability (PDP) and to reach a higher level of reliability. This article proposed a cross-layer strategy that combines the novel queuing model dynamic Markov Modulated Poisson Process (dMMPP) with AMC at the physical layer to ensure the QoS to the admitted uses in the channel. Simulation results prove that the cross-layer design combined with queuing offers better throughput and optimized delay over a channel during the call.

Keywords: Dynamic Markov Modulated Poisson Process (dMMPP), Average Delay, Packet Error Rate, Packet Dropping Probability, Throughput, FSMC

Introduction

Queuing theory finds an assortment of applications, such as media transmission, biomedical health monitoring, etc. Among the existing queuing models, analyzing a variety of traffic loads, the most standout model is Markov Modulated Poisson Process (MMPP).

Significant research has been carried out in MMPP through Continuous Time Markov Chain (CTMC) and Discrete Time Markov Chain (DTMC) (Al-Sayed *et al*., 2016; Mediouni *et al*., 2018; Amini *et al*., 2018; Wilson *et al*., 2018; Pashmforoush and Emrani Zarandi, 2021; Casado-Vara *et al*., 2019). The authors have analyzed and exhibited different outcomes of the systems, such as packet-dropping probability, average throughput, queue length, and delay in service. Another road map was created to analyze the joint effect of the finite length of queuing with AMC over wireless networks and presented a general analytical procedure to obtain the average spectral efficiency, average throughput, and packet error rate (Alnwaimi and Boujemaa, 2018). The packet's arrival was formulated using the Poisson process and the Finite State Markov Chain (FSMC) was used to obtain the transition matrix for AMC. At the same time, a joint effect of AMC with queuing has been analyzed with the deadline-constrained traffic for Multi-Input Multi-Output (MIMO) systems was proposed (Sutton *et al*., 2019; Liu *et al*., 2005). The Space Time Block Coding (STBC) in Nakagami fading channels was explored with the packet loss rate, throughput, and delay-bound violation probability.

Another STBC-based cross-layer design has been developed by Sheng Zhou *et al*. for queuing with AMC in MIMO systems (Liu *et al*., 2005). Two types of systems, namely Bell Laboratories Layered Space-Time (BLAST) and STBC have been analyzed and compared along with AMC. The authors observed the new trade-off between multiplexing and diversity in terms of delay and packet loss rate. An alternate cross-layer design was developed for STBC by finite-length queuing along with AMC under zero-forcing detection for MIMO systems (Alqahtani, 2018). The PER was optimized with this cross-layer design with the specified QoS constraints. At the same time, it is a must to study the framework that analyzes the AMC along with queuing for a single-user and multi-user scenario for Voice over Internet Protocol (VoIP) services in wireless networks (Amjad *et al*., 2019). The authors formulated a two-dimensional DTMC based on an MMPP to select the best modulation and coding through the transition probability. To formulate the transition probability, a study was conducted on the multi-hop relaying in wireless networks to handle the maximum arrival of packets (PalunčIć *et al*., 2018). An equivalent FSMC model with two hops, Decode and Forward (DF) imparting wireless channel, was proposed with AMC in queuing analysis. Queuing delay, packet loss rate, and average throughput were the performance metrics.

The dynamic behavior of queuing with AMC was analyzed in two different modes, called sleep mode and wake-up mode (Dezfouli *et al*., 2018). The formulated optimization problem considers delay, packet loss rate, and energy efficiency with low transmit power. A single-source single, destination-cooperative wireless communication system with multiple relays has been studied (Lin *et al*., 2019). The model was proposed with Additive White Gaussian Noise (AWGN) and fading with Nakagami-m. The arrival of bursty packets was modeled with MMPP. The queuing model has been generalized by discrete-time M/G/1 type at the source. The AMC has been adopted with four different modulation techniques with convolutional coding under dynamic traffic conditions. Another framework was proposed by considering the finite length queuing in wireless systems with AMC for multi-user VoIP (Lee and Cho, 2009). An uplink VoIP system has been formulated with a two-dimensional DTMC-based MMPP for multimedia services. Modulation and Coding Selection (MCS) has been derived as an integrated part of this system through the transition probabilities with a single user. With the help of this transition matrix, the dropping probability, PER, throughput, and spectral efficiency are obtained through AMC. Finally, a cross-layer design is established to lessen the PER in the queue recursion by optimizing the parameters in the physical layer. A cross-layer paradigm was discussed for transmitting MMPP over the Nakagami fading channel (Wang *et al*., 2020). This algorithm mainly focuses on energy efficiency, average throughput, and delay constraints with considering the spectral efficiency of the system. To maximize the spectral efficiency through the Modulation and Coding Scheme (MCS), another self-explanatory reinforcement learning framework was proposed by comparing it with the conventional look-up table and link adaptation in the outer loop (Saxena and Jaldén, 2020). Alternatively, the research carried out with AMC so far imagines that the status of the queue is always full, but the buffer in the data link layer was not engaged. Therefore, significant research must be done based on the FSMC model, which needs more fitting parameters for dynamic variation over the channels.

Queuing Process

The current AMC includes Binary Phase Shifting keying (coding rate ½), Quadrature Phase Shift Keying (with coding rate ½ and ¾), and QAM with $M = 16$ and 64 (with coding rate ¾). But the AMC discussed in the literature works well when there is no overflow in the queuing at the buffer. If overflow occurs in queuing, the AMC must be considered along with queuing to reduce the PDP and PER to achieve the desired throughput and spectral efficiency. This study considers the end-to-end connection of a wireless system model proposed by Liu *et al*. (2005) with two layers that combine the AMC with queuing. A queue with finite length is deployed at the transmitter that operates under First in, First Out (FIFO) mode. The receiver is employed with an AMC selector that selects the best modulation and coding based on the channel condition. The AMC controller implemented at the transmitter listens to the feedback channel and allocates the AMC based on the feedback acknowledged from the AMC selector.

Due to the swift development of multimedia-based wireless networks, users are no longer satisfied with video streaming and faster data transfer.

The packet loss probability and spectral efficiency performance are also poor due to the latency in the network. Therefore, the packets in the network have to be formulated through proper queuing and forwarding. Though AMC offers good spectral efficiency, it works well only when there is no overflow in the buffer. Hence, a need arises to study queuing and AMC to attain a high data rate with excellent spectral efficiency. The proposed method presents an alternative model for MMPP, known as dMMPP. The combined effect of finite length queuing with AMC has been analyzed using the dMMPP model through cross-layer integration. The dMMPP model has been developed based on the DTMC along with MCS for single-user scenarios and multi-user scenarios. Generally, MMPP is more qualified as an arrival process in survival calculations and programming for queuing models than the Poisson process.

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Specifically, although the MMPP/D/1 queue falls into the general "M/G/1" design, the general structure requires more variables and calculations while forming the transition probability matrix. These challenges have been addressed in dMMPP. The proposed dMMPP closely follows the MMPP in most aspects except the transition probabilities. A Markov Modulated Poisson Process is a Poisson process whose rate variation depends on a Markov process. In this process, the intervals between the successive events are independent and are distributed identically with exponential random variables. A general MMPP model can be defined by two states for the arrival and distribution process (Ciucu *et al*., 2019; Nasralla, 2020; Castellanos-Lopez *et al*., 2018; Carvalho *et al*., 2020; Marwat *et al*., 2018; Mota *et al*., 2019; Wang *et al*., 2015). Figure 1 shows the state diagram of the MMPP model, where:

λ_1 = The arrival rate in state 1
λ_1 = The arrival rate in state 2
q_{12} = The probability of transmission from state 1-state 2
q_{21} = The probability of transmission from state 2-state 1

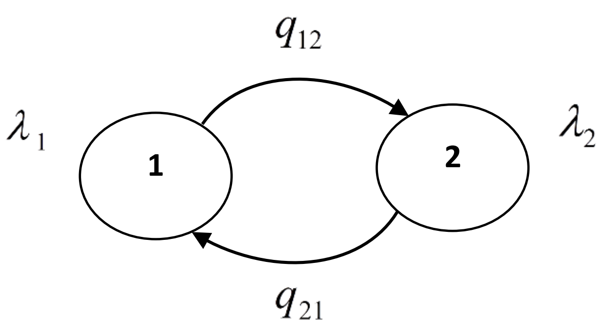

Fig. 1: State diagram of MMPP

Input: Beginning of time slot t (No of available packets = B_{t-1})
Output: End of time slot t and beginning of time slot t+1
procedure: Beginning of time slot t (No of available packets = B_{t-1})
No of available packets = B_{t-1} - C_t
if P_t < Available slots (E_t), then
P_t packets will be accommodated
$B_t = P_t$
else
E_t packets will be accommodated
$P_t - E_t$ packets will be dropped
$B_t = E_t$
end
end procedure: *End* of time slot t and beginning of time slot t+1

Fig. 2: Pseudo algorithm of MMPP

In this MMPP, the arrivals are modeled with two-state processes to discover the impact of bursty characteristics on the system performance. The packet's arrival and service rates are expected to follow the Poisson process. The packets arrived are serviced at the rate of. This MMPP allows the correlations between inter-arrivals of packets. Using all these parameters, the average arrival rate of the packets is determined by:

$$\bar{\lambda} = \frac{q_{21}}{q_{12}+q_{21}}\lambda_1 + \frac{q_{12}}{q_{12}+q_{21}}\lambda_2 \tag{1}$$

In a two-state MMPP model, the arrival rate is determined by these four distinct parameters. To assess the effect of bursty characteristics of arrivals of packets, one assumption must be made in MMPP. This supposition involves equating the arrival rate of packets in MMPP with the arrival rate of packets in the Poisson model. While considering the MMPP as a normal Poisson process in terms of arrival rates, it leads to ambiguity in the estimation of parameters throughout the queuing process. Another problem in MMPP is that it is mandatory to estimate the values of the mean arrival rate at each state and from one state to another state.

Evaluating all these parameters from the samples of traffic is much more complicated, especially when the number of states is unknown before starting the process. Hence, it is necessary to design a model that will predict accurate characteristics of the arrival process with low complexity. The Queuing arrival process and service process are analyzed in this section to construct the transition matrix for stationary distribution. First, queue state recursion is obtained based on the lemma proposed in (Alnwaimi and Boujemaa, 2018) and then the transition matrix will be defined based on dMMPP. The queue state recursion process is explained through the M/D/1/K queue model with the help of the flow chart depicted in Fig. 2. Let t be the time index, X_t represents the number of packets arrived at time t with a mean arrival rate of λT and K refers the size of the buffer. Let C_t indicates the number of packets to be transmitted using MCS at time t and B_t defines the queue state at the end of time slot t. Now, after moving packets from the queue, the number of packets to be processed in the queue is:

$$L_t = \max\left\{0, B_{t-1} - C_t\right\} \tag{2}$$

The number of free slots available in the queue at the time t is:

$$E_t = K - L_t = K - \max\left\{0, B_{t-1} - C_t\right\} \tag{3}$$

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Let be the number of packets arriving at the buffer at time *t*. If the number of arriving packets (P_t) is less than the available free slots in the queue (then all the arriving packets will be accommodated in the queue and then it will be processed. If the number of arriving packets (P_t) is more than the available free slots in the queue (E_t), the only number of packets will be accommodated and P_t - E_t the number of packets will be dropped and declared as lost. Hence the dropping probability will get increased. The dropping probability can be reduced with the help of the proposed dMMPP queuing process.

Dmmpp Model

In the MMPP queue recursion process, the packets are dropped randomly and they will be proclaimed as lost. While the packets are dropped randomly, sometimes the packets with low error rates might be lost and the packets with high error rates might be held. To avoid this, a dynamic strategy has been formulated to reduce the dropping probability of the packets received. The incoming packets are admitted into the queue based on two important parameters. They are:

- *SNR* of the received packets and
- The ratio of the service rate (μ_n) to arrival rate (λ_n) at any state

While the packets are being received at the buffer, the average *SNR* of the incoming packets will be figured. The packets with fair *SNR* will be considered for the queue process, while the packets with poor *SNR* will be discarded. The ratio of the service rate to the arrival rate denoted by 'α' will be calculated at each state. If this ratio is above the defined threshold 'αth', then the packets will be accepted otherwise, the packets will be dropped and declared as lost. This process is explained in the flow chart depicted in the algorithm depicted in Fig. 3.
The average *SNR* of the packets is calculated by:

$$\bar{\gamma}_p = \gamma_t \frac{\sum_{i=1}^{N}\left(1/\delta_i\right)}{N} \tag{4}$$

where, γ_t is the *SNR* level at the transmitter, is the interference factor at the receiver side and *N* is the total number of packets. The arrival rate threshold is calculated by:

$$a_{th} \frac{\sum_{i=1}^{K}\left(\mu_i / \lambda_i\right)}{\sum_{i=1}^{K}\mu_i} \tag{5}$$

Let, P_{SNR} denotes the probability that the *SNR* of the packet is more than the average *SNR* and P_a is the probability that the *a* is greater than the a_{th} then the packet dropping probability of the M/D/1/K queue model is given by:

procedure: Packets Arriving
  Calculate the SNR
  if *SNR* > Average, then
    Calculate $a = \frac{\mu}{\lambda}$
    if $\alpha > \alpha_{th}$, then
      Admit the packet
    else
      Discard Packet
      Calculate P_d
    end
  else
    Discard Packet
    Calculate P_d
  end
end procedure

Fig. 3: Pseudo algorithm of dMMPP

$$P_d = \frac{Number\,of\;\; packet\,dropped}{Total\;No\,of\;\; packet\,arrived} = \left(1 - P_{SNR}\right) \tag{6}$$

where:

$$P_{SNR} = \left\{\left(\frac{\bar{\gamma}_p - \gamma_t}{\gamma_p}\right)\left(1 - P_t\right)^k; \quad 0 \le k \le K; \text{otherwise}\right. \tag{7}$$

Let us assume the *N* number of packets is multiplexed at the port and the buffer has the finite capacity of *K* cells. During the time slot, a call may be in an idle or active state. Let us imagine that the system in state E_t and P_t packets are arriving (where *Pt*>*Et*) at slot k. Now the state moves to another new state with *k*+1. Let be the incoming traffic states with different AMC and indicates the probability of transition from the state of to the state of. The state transition occurs only in between the adjacent states of the model. The elements of the transition probability matrix can be derived by the Maximum Likelihood Estimation (MLE):

$$P_{ij} = \frac{number\,of\;transition\;from\,i\,to\;j}{number\,of\;transition\,out\,of\;i} \tag{8}$$

Based on the ML estimation, the MCS level matrix of transition probability under the Markov process is given by Liu *et al*. (2005):

$$P^s = \begin{bmatrix} P_{s1,s1} & P_{s1,s2} & \cdots & P_{s1,sK} \\ P_{s2,s1} & P_{s2,s2} & \cdots & P_{s2,sK} \\ \vdots & \vdots & & \vdots \\ P_{s1,K} & P_{s2,sK} & \cdots & P_{sK,sK} \end{bmatrix} \tag{9}$$

where, $P^s = \dfrac{e^{-\lambda}\lambda^s}{s!}$ and also $\sum_{i=1}^{K} P_{s_i s_j}$ and K is the size of the buffer. Each state in the matrix denotes the probability to stay with that MCS based on the boundary defined by SNR. In the MCS level transition matrix, the transition will occur only in between adjacent states i.e., the probability of transition that exceeds more than two states is zero:

$$P_{s_i, s_j} = 0; |i - j| \geq 2 \tag{10}$$

Now, the transition probability of retaining in the same MCS level is defined by:

$$P_{n,n} = \begin{Bmatrix} 1 - P_{1,2};\ n = 1 \\ \sum_{n=E_t+1}^{K} \dfrac{P_{SNR}(n)}{Kn}; 1 < n < K \\ 1 - P_{K,K-1};\ n = K \end{Bmatrix} \tag{11}$$

Let represents the distribution of queue length over a slot k and it can be obtained by:

$$\psi(k+1) = \psi(k) P_{n,n}(k) \tag{12}$$

Now the Packet loss rate of the channel can be obtained while the active calls change over time t:

$$P_o(n) = \sum_{i=0}^{K} \psi(n) \frac{\sum_{j=0}^{i} \max(P_{n,n}(j), 0)}{\sum_{k=0}^{j} P_{n,n}(k)} \tag{13}$$

Also, a packet from the source will reach the destination with the probability of. The total packet loss rate at the destination as defined by Alnwaimi and Boujemaa (2018) is as follows:

$$\varepsilon = 1 - \left((1 - P_d)(1 - P_0)\right) \tag{14}$$

The average throughput is defined by:

$$\eta = 1 - \varepsilon = (1 - P_d)(1 - P_0) \tag{15}$$

The average throughput based on the arrival rate of the queue state is given by:

$$\eta_f = (\lambda T_f)(1 - \varepsilon) = (\lambda T_f)(1 - P_d)(1 - P_0) \tag{16}$$

The dMMPP queuing model is coupled with queuing for each channel state and the PER is obtained at the end of each transit time. Each packet is affected by noise in a different way. Therefore, the PER can be alternatively evaluated by the ratio of the time-average number of erroneous packets to the time-average number of arriving packets (erroneous packets include dropped and corrupted by channel noise).

Materials and Methods

The process employed here is purely based on the time slot. The incoming packets follow dMMPP and arrive at the buffer of size K. When the buffer is completely occupied, all the arriving packets will be dropped and declared as lost. The role of the AMC controller on the transmitter side is to control the servers and calculate the service rate to process the packets in the queue based on the feedback information received from the receiver. In AMC, the available transmission modes with different service rates will be assigned to each state in the MCS transition matrix. This transition matrix is updated after the transmission of the set of N frames. Based on the available transmission modes, the boundary points of AMC are determined by fixing the threshold. Once the boundary points are obtained, the state transition matrix with the dMMPP queuing process is determined by Eq. (11). The AMC selector will select the optimized modulation and coding based on the CSI received. Finally, the served packets departed from the queue will be encoded by the convolutional encoder and will be converted into frames. At the receiver end, these frames are again converted back into packets and decoded to recover the original packets. To achieve the cross-layer integration, the buffer size (K), arrival rate, and frame duration are fixed to optimize the PER in AMC which maximizes the throughput. These mentioned steps are repeated and the MCS transition matrix will be updated on a slot-by-slot basis. To optimize the parameters in the physical layer, the parameters of the MAC layer will be updated based on the feedback received from the physical layer. In this way, the cross-layer design is achieved to optimize the performance of queuing model with AMC.

Results and Discussion

The performance of the queuing process is measured in two different cases. The first case is the training or reference case in which the traffic components are described by a simple 2-state dMMPP (without AMC) with different parameters. Another case is tracking phase investigated under the multiple-state dMMPP (with AMC). The performance of the developed queuing model is simulated under Qualnet, a global network simulator, and MATLAB.

The number of packets assigned to transmit under the references case is 6000, with the size of each packet being 1080 bits as depicted in Tables 1-2. Figure 4

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illustrates the average delay of the dMMPP queuing with different SNRs at the sink node in 100 sec under the reference case. The lambda algorithm has been used to formulate the traffic raised in dMMPP and the corresponding arrival rate is plotted as vertical bars with the time. When the SNR is maximum, the packets are serviced faster and hence the average delay of the departure of the packet from the queue is reduced marginally. The figure clearly shows that the dMMPP queuing model reduces the average delay significantly with increasing SNR. From the figure, it is apparent that the average delay of packets is decreased by more than 40% in dMMPP when benchmarking with MMPP and CMMPP queuing models.

Figure 5 clearly portrays the fact that the packet-dropping probability of the proposed dMMPP model through simulation closely follows the theoretical values obtained through the equations. Figure 5 compares the packet-dropping probability of the dMMPP model with that of MMPP and CMMPP.

Table 1: Simulation parameters (reference)

Parameter	Value
Channel bandwidth	200 MHz
Packet length (N_b)	1080 bits
f_d	10 Hz
Buffer size (K)	100 Packets
Average SNR $\bar{\gamma}$	2-18 dB

Table 2: Simulation parameters (tracking)

Parameter	Value
Channel bandwidth	200 MHz
Fading factor	m = 1
Frame length/ Slot duration	2 ms
Packet length (N_b)	1080 bits
f_d	10 Hz
Buffer size *(K)*	100 Packets
Poisson arrival rate (λT_f)	2 and 4
Service rate	1 per slot (500 packets/sec)

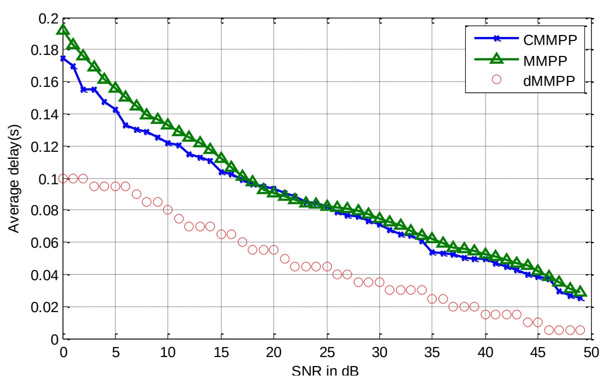

Fig. 4: Average delay with SNR

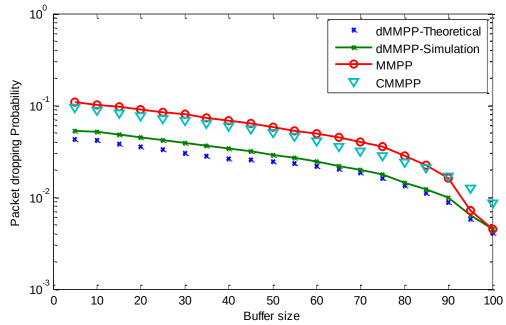

Fig. 5: Packet dropping probability with buffer size

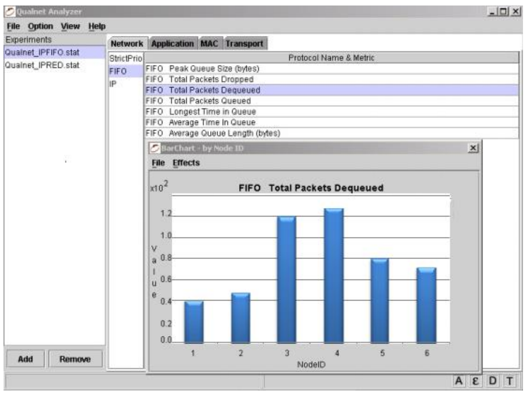

Fig. 6: Packets dequeued in MMPP

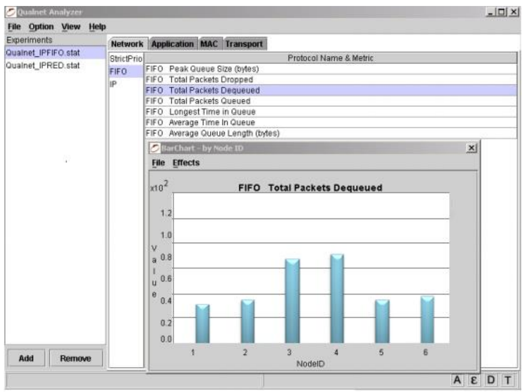

Fig. 7: Packets dequeued in CMMPP

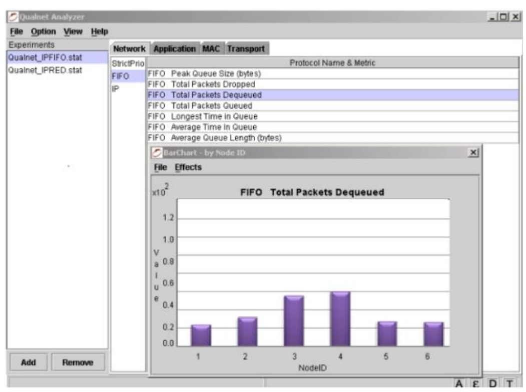

Fig. 8: Packets dequeued in dMMPP

Table 3: Target packet error rate vs packet error rate

Case (SNR = 20 dB)	dMMPP with AMC Minimum (optimum) PER	Corresponding target PER	Maximum (worst) PER	Corresponding target PER
$\lambda T_f = 4$ and K = 50	0.0090	0.0030	0.0260	0.0116
$\lambda T_f = 2$ and K = 50	0.0039	0.0036	0.0144	0.0113
$\lambda T_f = 4$ and K = 100	0.0018	0.0044	0.0093	0.0129
$\lambda T_f = 2$ and K = 100	0.0007	0.0053	0.0074	0.0153

The dMMPP queuing model achieves the least packet-dropping probability (more than 5%) than the MMPP queuing model for different buffer sizes. Figures 6-8 display the number of packets dequeued from the queue at different nodes due to its service rate at low SNR of 4 dB in MMPP, CMMPP, and dMMPP respectively. For example, at node 3, the number of packets dequeued in the MMPP model is 1200, the number of packets dequeued in CMMPP is 700 and the number of packets dequeued in dMMPP is around 500. From these figures, it is deliberate that the number of packets dequeued in the dMMPP queue process is very low when compared to that of the MMPP and CMPP queuing model even at low SNR.

Performance Of Dmmpp Queuing Model With Amc

In this segment, the performance of the dMMPP queuing model is validated along with the AMC through the cross-layer design. The metrics analyzed are packet error rate, average delay, packet dropping probability, and throughput.

As mentioned in the previous section, the modes with five modulation techniques and with different rates are adopted with the AMC selector. Once the MCS is adopted, the MCS transition matrix will be updated based on Eqs. (6-11). The system performance is evaluated with the nakagami fading model with a 1 km simulation area. Figure 10 shows the target packet error rate against the packet error rate of the dMMPP queuing process with AMC. The reference parameters of queuing are fixed and the optimization parameters of AMC were obtained through the simulation.

Figure 9. Target packet error rate vs packet error rate from Fig. 9, it is observed that when the buffer size is increased, the PER can be reduced against the target packet error rate P_o. The PER can be reduced by reducing the arrival rate of the packets also. The optimized value of the target packet error rate (given in Table 3) is found in this figure and it can be fixed as the target packet error rate for further transmission. Here, the PER of each curve holds the maximum value of 0.0260 at the target packet error rate of 0.0116. From this measure, it is suggested that the target PER (P_o) can be set as 0.0016 for the worst case. Similarly, the minimum value of PER is 0.0007 at P_o = 0.0053. Hence the optimized merit of the target packet error rate Po can be set as 0.0053 for further transmission. Here the optimized value of P_o is one of the solutions for the cross-layer design between AMC and queuing. If the optimized target PER is less than 0.0116, then the packet-dropping probability will get increased and hence the throughput will be reduced. Table 3 has been developed from Fig. 9. Table 3, it is apparent that the proposed queuing process with AMC yields the minimum PER with optimized target PER when compared to the MMPP queuing process. Next, the packet-dropping probability due to the buffer overflow in MMPP and dMMPP is analyzed against the system load. The packet-dropping probability has been derived for the buffer sizes of 50 and 100 packets and is validated in Fig. 10. From the figure, it is observed that when the system load increases, more packets will be dropped and hence the packet-dropping probability also increases. The packet-dropping probability reached the maximum value of 0.1 with a maximum system load of '1'. The figure reveals that the proposed dMMPP queuing process controls the packet-dropping probability better than the MMPP with the increasing system load. The minimum packet-dropping probability of the dMMPP queuing process is around, whereas, in the MMPP queuing process, it is around 10-5. The packet dropping probability can be controlled by avoiding the overflow by increasing the buffer size, in the figure.

Figure 11 depicts the packet error rate with system load for the proposed queuing process with AMC. Here, the simulator computes the packet error rate with the help of the duration of the frames and the power level of interference during the transmission. The packet error rate of the dMMPP queuing process will possess values in the range of 0.01-0.100 when the AMC was not integrated with queuing through cross-layer design. The packet error rate will fall into the range of 0.00025-0.002 when the AMC is integrated with queuing process through cross-layer design. The cross-layer design is achieved here with the help of the target packet error rate discussed in the previous section. Figure 12 reveals the behavior of throughput with the system load. The throughput is calculated in terms of the number of packets per slot. The throughput of the MMPP and dMMPP queuing processes are compared with buffer sizes of 50 and 100. From the figure, it is observed that the gaps between the curves are obvious when the system load is increased. The proposed dMMPP queuing process yields better throughput when compared to the MMPP queuing process. The differences in throughput between MMPP and dMMPP reach more than 0.2 packets/slot. To manage the load in the queuing process, the size of the buffer can be increased to achieve better throughput. At the same time, increasing the buffer size will affect the system's scalability, which degrades the system's performance.

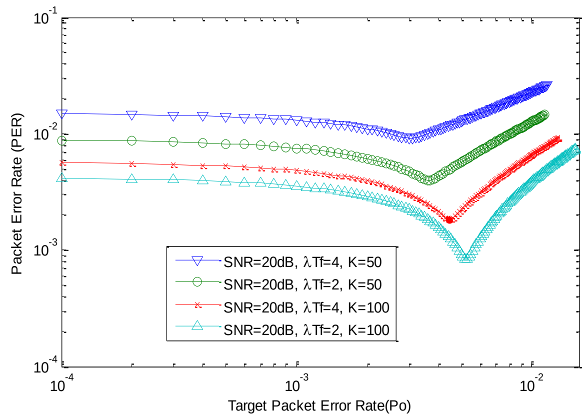

Fig. 9: Target packet error rate vs packet error rate

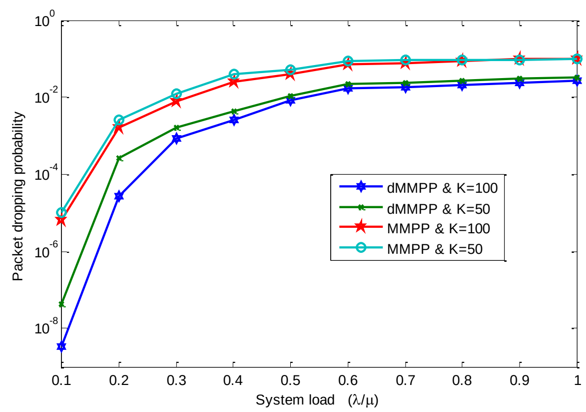

Fig. 10: System load vs packet dropping probability

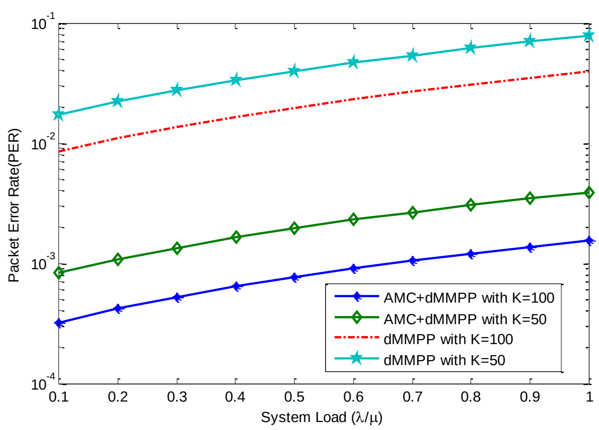

Fig. 11: System load vs packet error rate

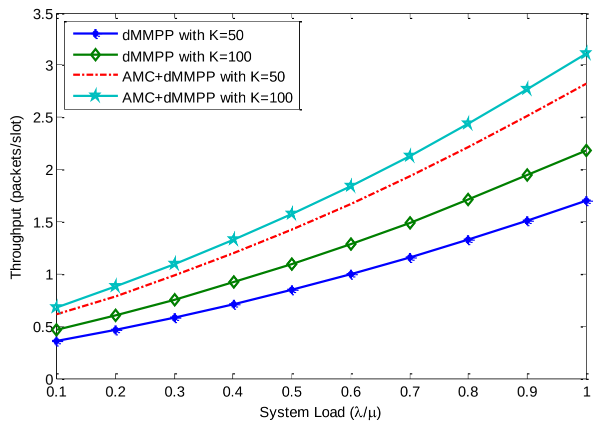

Fig. 12: System load vs throughput

Conclusion

In this study, a novel dMMPP queuing process has been proposed and combined with AMC to achieve cross-layer integration for wireless networks. The behavior of the queuing model is analyzed with the presence and absence of AMC and the results are compared with the MMPP and CMMPP queuing models. To regulate the packets arrived at the data link layer, the array of AMC with different service rates is considered to improve the performance of the system through cross-layer design. The cross-layer design is achieved between the MCS in the physical layer and the packet arrival and service process in the data link layer. The performance of the proposed system is validated through the average delay, packet error rate, packet dropping probability, and throughput. Through the simulation, the optimum value of the target packet error rate is obtained to control the packet error rate as a minimum even though the arrivals are bursty in nature. The results clearly reveal that the proposed queuing process has a dominant role in the system performance. Further, this queuing process can be continued for non-coherent methods for mobile users under different QoS requirements.

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Author's Contributions

Manikandan Arunachalam: Conceptualization and content written.

Naresh Kumar Babu: Methodology.
Anandan Perumal: Validation.
Ramprasad Ohnu Ganeshbabu: Reviewed.
Jai Ganesh Balasubramanian: Literature reviewed and current state of research.

Ethics

This article is original and contains unpublished material. The authors confirmed that the manuscript reviewed thoroughly, and no ethical issues involved.

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