EMULSIoN: Environment Mitigation on mULtimedia StreamIng Networks

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***Abstract*— Handover algorithms typically operate by assigning preconfigured threshold or weight values onto network performance metrics such as delay, data loss and signal strength. Such approaches are performance limited as they do not consider external factors that affect the network such as the physical environment and current weather conditions. Previous research illustrates that foliage density combined with detrimental weather conditions can have degrading effects on wireless links. The changes to these environmental factors over long vehicular-based mobile user sessions can lead to sub-optimal handover decisions and a negative impact on a user's Quality of Experience during mobile video streaming. There is need for a handover approach that adapts to these factors and mitigates any negative effects that occur. This paper proposes a method for Environmental factor Mitigation on mULtimedia StreamIng Networks (EMULSIoN). EMULSIoN uses a perceptron artificial neural network approach to mitigate the latency and delays caused by environmental factors. Using dynamic network performance metrics and with known topographical data, the EMULSIoN directed learning approach can learn from previous user sessions to mitigate these environmental effects. EMULSIoN further uses GPS and topographical data to divide vehicular routes into small sub-areas for optimal performance in varied terrain. Results illustrate that EMULSIoN has significant video quality improvements in comparison to pre-configured weight handover strategies.**

Keywords-- Artificial Neural Network; Feed Forward Learning; Heterogeneous Networking; Vehicular Mobility; Multimedia

I. INTRODUCTION

Environmental factors are difficult to properly consider in large scale heterogeneous topologies. Foliage is a physical obstacle, but unlike other physical obstacles such as buildings, the density of foliage is ever changing. This is due to factors such as time of year and wind speed. In vehicular scenarios, varied terrain types can cause fluctuations in a network's Received Signal Strength (RSS). These fluctuations affect handover decisions and their frequency, which have a subsequent effect on user experience when streaming multimedia data. Handover strategies have been proposed to optimize the Quality of Experience (QoE) for mobile users [1], but there has been a lack of work that considers underlying environmental factors [2][3][4]. Traditional approaches towards maintaining network connectivity [1] apply either static thresholds or pre-configured weights onto dynamic network performance metrics. This approach is not suitable in environments where varying amounts of interference are generated. Variable interference causes noticeable performance fluctuations and playback stalling during multimedia streaming sessions. Un-optimized handover decisions also become more common due to access points being in competition and causing a "Ping-Pong" effect to occur.

The EMULSIoN handover architecture is proposed to address such issues. EMULSIoN is a performance prediction based Artificial Neural Network (ANN) which is novel in comparison to existing mechanisms as it further considers environmental factors. EMULSIoN is "pluggable" as it can be reconfigured to measure overall performance using different metrics, such as a calculated Mean Opinion Score (MOS) for video quality. Vehicular environments are ideal for training EMULSIoN's ANN as the cyclical nature of vehicular movement enables network performance prediction.

EMULSIoN has been evaluated across five simulated environmental scenarios. Each scenario has different weather conditions and foliage densities applied onto a vehicular route. Performance evaluation shows that EMULSIoN outperforms pre-configured weight handover approaches in terms of visual quality in streamed multimedia. Quality degradations caused by interference are mitigated and a level of video quality is maintained throughout the user's journey.

This paper is organized as follows: Section II presents a literature review on handover strategies for optimizing the QoE for mobile users as well as an analysis of the effects of wind/foliage on network performance. Section III details the experimental setup and software used to generate the results data discussed in Section IV. The conclusions of the results are outlined in Section V.

II. RELATED WORK

Environmental factors can play a huge part in signal degradation [2]-[6]. [2] Discusses Ricean k-factors and wireless signals. It is explained how signal strength is subject to significant interference as it passes through physical obstacles on the transmission path, culminating in interference when it reaches the receiver. Wind-blown foliage is outlined as a significant obstacle to signal propagation. The work in [3] analysed the effects of various wind speeds on a wireless sensor network. It is shown that wind has a negligible effect on RSS; and only becomes a factor when dense foliage is present. The longitudinal studies conducted in [4] described the effects of wind-induced fading on wireless connections. It is illustrated that the effect of wind and foliage on signal transmission can vary immensely depending on factors such as time of year and wind velocity. The findings in [5] concur with the conclusion reached by [4] in that wind direction as well as its speed determines the extent of fluctuations that a wireless signal experiences. A simulation model is also proposed to illustrate the effects of swaying vegetation on signal fading for fixed network positioning in rural sub-urban areas. The k-factor measurements in different environmental conditions will serve as inputs for the experiments presented in this work. The work in [7] shows the results of several RSS measurements within a sub-urban environment. The notable conclusion from this work is that while degradation is experienced in each signal path, one path had less severe fluctuations due to the wind's direction. The conclusion drawn from this was that wind direction can also mitigate degradations through reducing foliage density.

Handover strategies have also been a subject of discussion in ensuring optimal QoE in mobile scenarios. The researchers in [8] analysed the degradations that can occur on video quality in pedestrian and train movement. Results presented showed that handover overhead increased along with degraded video quality for a train scenario compared against a pedestrian scenario. This work highlights the need for a QoE strategy for high velocity scenarios. The work in [9] presents a network selection algorithm that considers user location as well as velocity when optimizing QoE. The work presented in [10] proposes a static threshold approach that minimises handover overhead when streaming by monitoring RSS and using scalable video coding in order to minimise interruption. While the results do show an improvement over traditional handovers, its benefits may be mitigated in degrading environmental scenarios due to its reliance on RSS. A solution illustrated in [11] considers the primary data type being received when initiating handover. The work uses fuzzy logic to match the QoS and data rate requirements for a particular data type. An example of this is high speed connections for high-definition video streaming. Future work will consider mobile user factors such as distance and velocity. As such, it does not consider environmental based interference. The proposal in [12] illustrates an extension on the Media Independent Handover (MIH) standard to include more QoE awareness, seamless mobility and data-type adaptation. This changes the handover strategy depending on the data stream. [13] And [14] are other examples of QoE experience focused handover architecture. Their aim is to have multimedia users always connected to the most suitable network for best QoE. Test results of the proposed architectures so far have demonstrated a large improvement in performance over traditional approaches.

The major limitation of related work in this area is that the potential interference in the user's surrounding environment is not properly considered in handover decisions. The literature supports that weather and environment can affect network transmissions and can therefore affect handover strategies that consider signal strength. The EMULSIoN architecture aims to mitigate these effects by considering the local geography when making a handover decision.

III. EMULSIoN ARCHITECTURE

This section describes the EMULSIoN handover architecture. EMULSIoN uses a perceptron artificial neural network approach to mitigate quality degradations and playback stalling caused by un-optimized handover decisions due to environmental factors. The EMULSIoN architecture assigns different training weights for different types of network traffic and can re-evaluate itself to a different training set and overall performance indicator when the primary traffic being received has changed. The algorithm considers topographical data, previous user experience as well as dynamic network performance metrics when implementing a handover decision.

The EMULSIoN architecture is deployed as an application on the mobile device. EMULSIoN uses Stream Control Transmission Protocol (SCTP) to ensure a fast soft-handover. This reduces overhead and latency experienced when switching networks compared to using a traditional hard handover method. When deployed, EMULSIoN uses SCTP's multi-homing functionality to identify the most robust connection in range. This is designated the "back-up" connection, used when none of the high speed networks in range are considered suitable for streaming. Relying on this network comes with a cost to data speed and potential QoE. At intervals, the network topology is scanned to see if a more robust connection is available to serve as a fallback.

EMULSIoN's main features are its adaptive learning for different network environments and tolerance against changes occurring to the vehicular route. The algorithm considers *n* networks in range and a training set of weights *w* is assigned to each networks performance metrics. On a second by second basis, the designated performance metrics *x* to be monitored are taken in as inputs and each of their current values are normalized between 0 (an unacceptable value) and 100 (the best possible value). These inputs are multiplied by their training weights to obtain that network's dynamic score value n^{SCORE} as illustrated in Eqn 1.

$$n^{SCORE} = \sum_{i=1}^{number\ of\ inputs} (wi * xi) \tag{1}$$

The n^{SCORE} representing each network's suitability is compared against a defined threshold value Θ. A n^{SCORE} that exceeds Θ has its network considered as a handover candidate. If more than one candidate exceeds Θ, the network with highest n^{SCORE} is chosen. If no network score exceeds Θ, the user falls back to a designated backup network to maintain the session. For this paper, performance metrics are collected from each network in one second intervals. At the end of the training cycle, the overall performance is assessed and the weights are modified to encourage better performance in later cycles.

The extent of the weight modifications are decided by analyzing the linear regression of the overall performance metric. This is done by calculating the slope of the line for performance for the five most recent training cycles. This slope value is multiplied by a fixed learning rate and then applied onto the weight set. The learning rate parameter controls the size of weight changes during training. If the rate is too small or too high, the overall performance can be trapped within local maxima, where performance reaches a peak and cannot go higher. The learning rate settled on for these tests is 0.15; tests showed this was an ideal value for machine learning in a steady manner. To further avoid local maxima, weights are further incremented by a random decimal value between -0.2 to 0.2 every fifth cycle. Training is considered complete when the slope value reaches 0. This signifies that the ANN has reached an optimal weight allocation for that route.

```
//initiate Handover Decision
    void getHandoverDecision() {
    Double metric1, metric2, metric3
    int weightedsum

    for each(Networks) {
        int weightedSum = 0;
        weightedSum +=
(metric1*w1)+(metric2*w2)+(metric3*w3)
        if(weightedSum > networkThreshold)
            candidateNetwork.add(network)

        if(candidateNetwork.size == 0)
        handoverTo(backup)
    }
    network favourite
    for each(candidateNetwork)
        if(candidateNetwork > favourite)
            favourite = candidateNetwork
    handoverTo(favourite)

}
    //Train ANN at end of a cycle
    void initiateTraining() {
    double  slope = slopeOfLineCalc(historicResults)
    double correction = slope * learningRate
    if(correction == 0)
        training = false
    else
        for each (weights)
            weights+=correction
            if(cycleNum % 5 == 0)
                for each(weights)
                weights+= RandNum(-0.2,0.2)
    }
    //Plan out Route
    String route =
GPS.getCurrentPosition.getRouteName()

    sleep(5000)
    if(GPS.hasChanged())
        subRoute.inTransit = true
        if(GPS.getCoordinates() is NOT inside sub-
route area)
            if(new sub-route is existing sub-route)
            weights = subRoute.getWeights()
            else
            Look up new Sub-route and add to
subRoutes array

    While(Route.inTransit == true)
        getHandoverDecision()
        sleep(1000) //run on second by second basis
        overallThroughput += getMBReceived()
        if(Route.getEndPoint() ==
GPS.getCurrentPos())
            Route.inTransit = false
            historicResults.add(overallThroughput)
            initiateTraining()
```

Fig 1: Pseudo-code for EMULSIoN algorithm

A complication with vehicular routes is that a user may not necessarily traverse the entirety of that route on every journey. This can disrupt the training phase with incorrect weight modifications. Another potential issue is that training a median weight allocation to suit an entire route may return sub-optimal performance due to the weight allocation not considering the variation in fluctuations caused by changing terrain. To avoid this, EMULSIoN uses GPS and topographical data to divide an overall route into "sub-routes" as illustrated in Fig 2. Each sub-route is defined based on its overall terrain profile and are each trained with their own separate training sets. When a user traverses one sub-route and enters another, the weight allocation is then dynamically re-configured to the current training set for the now-current sub-route.

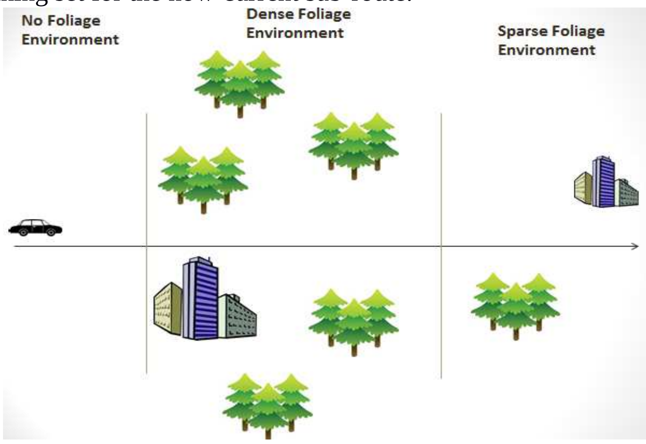

Fig 2: Example of a route being divided into sub-routes based on terrain profile

An example of video training is described in Table 1 the Mean Opinion Score (MOS) as the overall performance metric. The user is being streamed a media file from the internet in an environment with no foliage present. The first cycle of training with randomized starting weights results in a MOS score of 2.8, indicating below average video quality. The slope is then multiplied by the defined learning rate and returns a value of 0.42. This correction is added onto the weights for the next cycle increasing the likelihood of handing over to the high speed networks during the next training cycle. This continues until the slope value reaches 0 and training period ends.

TABLE 1: Example of video training for EMULSIoN in a "No Foliage" scenario

Cycle	w1	w2	w3	MOS	Slope	Correction	Learning Rate
1	0.2	0.1	0.15	2.8	2.8	0.42	0.15
2	0.62	0.52	0.57	3.44	1.72	0.258	0.15
3	0.878	0.778	0.828	3.4	0.3	0.045	0.15
4	0.923	0.823	0.873	3.4	0.176	0.0264	0.15
5	0.969	0.899	0.809	3.36	0.108	0.0162	0.15
6	0.985	0.915	0.825	3.36	-0.02	-0.003	0.15
7	0.982	0.912	0.822	3.36	-0.012	-0.018	0.15
8	0.98	0.91	0.820	3.36	-0.008	-0.0012	0.15
9	0.979	0.909	0.819	3.36	0	0	0.15

IV. RESULTS

A. *Simulation*

The network environment is created using the NS-3 network simulation framework. The simulation landscape as seen in Fig 3 is a recreation of the M50 motorway outside of Dublin, Ireland. This route is a varied terrain environment with areas of dense foliage present along the route that varies at different times of the year. Three high-speed WiMax access points (AP) are placed at designated points along the start, middle and end of the route. The high speed networks will be set up differently in two different sets of simulations. One set will have the high speed networks use QAM64 modulation (54 Mbps) and the other tests will use QAM16 (27.65 Mbps). A robust LTE connection broadcasting at QPSK modulation (13.82 Mbps) is designated as the backup connection by EMULSIoN in both cases. This connection's performance is inferior from the high-speed WiMax but is less susceptible to interference due to its lower data rate. Its effective coverage area covers the whole simulation area. Using this connection exclusively results in a stable performance but makes high quality video infeasible for streaming due to the low data rate and traffic. The ideal solution is to use high-speed connections when inside their effective coverage range and defer to the more robust backup connection otherwise. A comparison will be drawn between EMULSIoN's effectiveness in both modulation scenarios.

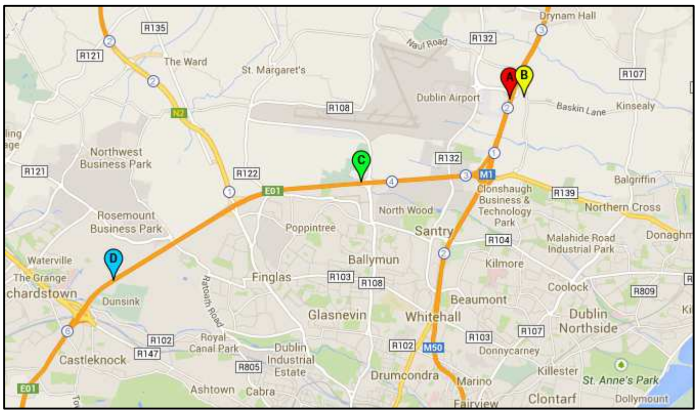

Fig 3: Points B, C and D are high-speed base-stations while A represents the starting point

For streaming video, the Evalvid [16] module was used. This NS-3 extension allows for streaming video files over simulated networks. Evalvid calculates the Peak Signal to Noise Ratio (PSNR) for the streamed video file. A quality comparison is done between the received video to the original file on a frame by frame basis. This is done by calculating the PSNR for the original video. This is the reference PSNR used as a benchmark for video quality. Evalvid generates dump files upon successful streaming at the receiver; these reconstruct the streamed video file along with any degradation's that have occurred. The file is then converted back to raw video data and its PSNR is compared to the benchmark PSNR to generate a MOS score. Although Evalvid is an objective method, future work shall be done using subjective analysis. Based off of degradation estimations presented in [5], EMULSIoN is trained under five different test cases:

1. *No foliage present on the path and no wind*. There is a clear Line-of-Sight (LOS) component for the duration.
2. *Sparse foliage with a low wind velocity*. There is an increase in obstacles present in the environment.
3. *Dense foliage along the route with a low wind velocity*. The foliage obstructions are much denser with LOS only when the user is in close proximity to the AP.
4. *Dense foliage with a strong wind velocity*. All signals that reach the receiver are diffused and interference is high.
5. *Varied terrain profile*. The foliage density and weather experienced changes during travel. Alternates between LOS and NLOS

The Environmental conditions are simulated using the Nakagami-m propagation loss model [15]. The model is ideal for simulating transmission signals travelling through foliated terrain [3] [4] [5].

B. *Wind Data*

The wind speed and foliage data used for these tests are based off of wireless k-factor estimates presented in [5]. It is illustrated that k-factor decreases as wind speed increases. The calculation of the wireless k-factor is described in Eqn 2 [5].

$$k = \frac{Power\ in\ constant\ part}{Power\ in\ random\ part} \tag{2}$$

The shape parameter *m* of the Nakagami model represents potential maximum fade depth in interference generated by the surrounding environment as illustrated by Eqn 3 [17].

$$m = (K^2 + 2K + 1)/(2K + 1) \tag{3}$$

C. *Result Data*

This section presents EMULSIoN for multimedia streaming. The algorithm was tested for QAM16 and QAM64 modulation strategies across four uniform terrain scenarios. A fifth environmental test with a varied terrain profile is also defined to test EMULSIoN's dynamic weight re-allocation in both modulations. The metrics used as inputs were w1=Loss, w2 = RSS and w3 = Jitter. The results presented in Fig 4 & Table 2 demonstrate how EMULSIoN outperforms a pre-configured strategy in terms of throughput. It can be seen that throughput increased in every uniform environment test case.

TABLE 2: Throughput comparison for Test Cases 1 - 4

		QAM64		QAM16	
	Case	Pre-config	EMULSIoN	Pre-config	EMULSIoN
No Foliage	1	1466	2542	1900	1981
Sparse Foliage	2	1400	2021	1800	1980
Dense Foliage	3	1150	1558	1750	1980
Dense Foliage/Wind	4	860	1310	1640	1776

Table 2 illustrates how the EMULSIoN algorithm has mitigated worst-case environmental interference. The weight allocation learned by EMULSIoN balances the usage of both the high-speed and robust networks with consideration for the scenario's terrain profile. The ability to switch directly to robust networks when WiMax network performance decreases means there is also a heavy reduction in periods of no service and heavy data loss. The user is guaranteed the best possible QoS throughout their journey. EMULSIoN is still effective even in scenarios were more robust data rates are used as can be seen in Table 2.

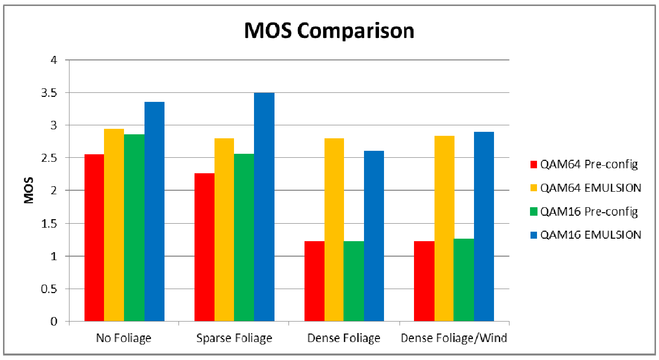

Fig 4: MOS comparison for all strategies and scenarios

For the uniform environment test cases, a ten minute long clip was streamed for the entirety of the ten minute journey. A more robust transmission may result in a seamless experience but the results seen in Fig 4 & Table 3 show EMULSIoN is capable of mitigating the larger degradations that can occur to streamed video on higher rates. This improvement on higher data rates means that low-bandwidth; high quality video codecs such as HEVC can be used without fear of major quality degradation. It can be seen in dense foliage environments that a pre-configured approach produces poor overall video quality. A MOS rank of 2 or lower indicates the received video would exhibit traits such as frame loss and high amounts of video artefacts. Even in the worst possible environmental conditions, EMULSIoN returns a video quality close to rank 3, indicating a watchable video with slight visible errors present.

TABLE 3: MOS comparison of uniform scenarios

	QAM64		QAM16	
	Pre-config	EMULSIoN	Pre-config	EMULSIoN
No Foliage	2.56	2.95	3.15	3.36
Sparse Foliage	1.23	2.8	3.04	3.5
Dense Foliage	1.22	2.8	2.1	2.6
Dense Foliage/Wind	1.22	2.84	1.8	2.9

Fig 5 details EMULSIoN's performance for the varied terrain scenario, in which the environment is composed of three different terrain profiles divided into sub-routes. A median weight allocation that attempts to optimize for the entire route across all three sub-routes may be detrimental towards overall QoS/QoE. The journey in this scenario starts with no surrounding foliage, and then enters a dense forested area with no LOS component before stopping in a sparse foliage area. The weights for each sub-route were assigned the weights of their corresponding uniform scenario for comparison. It can be seen that performance of the QAM16 links remains stable throughout the simulation with little to no degradation occurring. In this case, falling back to the backup link at the edge of cell coverage has allowed EMULSIoN to overshadow a pre-configured approach. For QAM64 data rates, the result is significantly different. The increased fluctuations in the environment in combination with the smaller coverage areas of the high-speed networks can cause long periods of latency in a pre-configured approach. EMULSIoN avoids this problem by instead making use of its designated fall-back network at these points instead. With this approach the overall potential throughput has raised significantly.

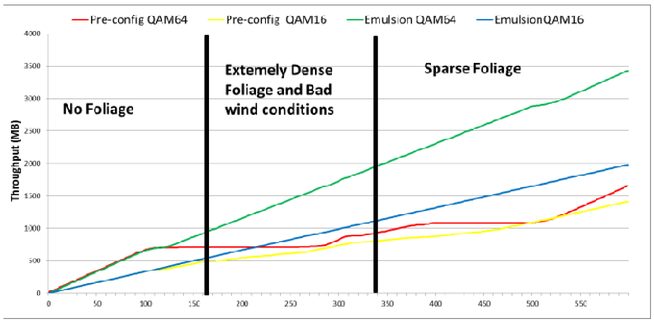

Fig 5: Throughput performance in the varied Environment scenario

Fig 6 & 7 shows the result of video streaming through the varied terrain environment. In this scenario, a one minute long clip is streamed at every 60 seconds along the route with the MOS score for each instance being calculated upon the journeys completion using Evalvid. This showcases how changing terrain profiles can affect video quality. For these tests, the weight allocation was dynamically shifted to the optimal weight allocation reached by the ANN in its respective uniform scenario. In practice, the weights are changed from high weights for the no foliage portion to low weights for the bad weather/dense foliage and to mid-high weights for the sparse foliage terrain. With this method, video quality remains at an adequate standard for the duration of the journey.

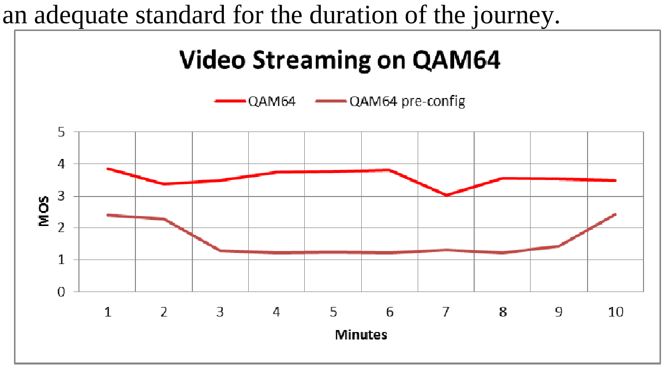

Fig 6: MOS performance on a minute by minute basis for QAM64

In Fig 6, video quality starts off high but decreases as the user approaches the edge of the high speed coverage area. This signifies fall-backs to the backup network becoming more frequent over time. When the user enters the worst case environment at the halfway mark, the MOS score drops to around 1. This is due to the video stream experiencing high levels of loss occurring. As the user enters the sparser foliage area, more time is spent again on the high speed networks and video quality increases. At no point in the scenario does the MOS score drop below 3, indicating the video will always be of adequate quality.

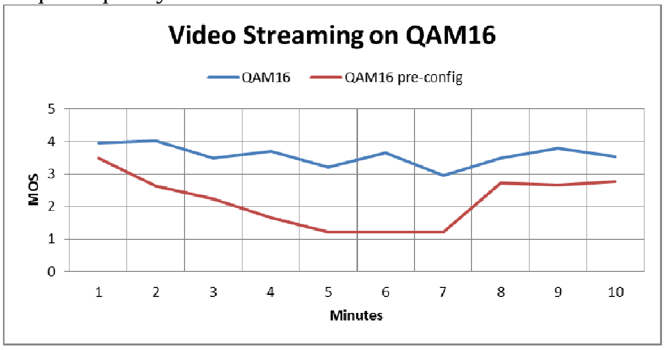

Fig 7: MOS performance on a minute by minute basis for QAM16

For the QAM16 scenario illustrated in Fig 7, performance is generally the same but with more fluctuation. The low weight values mean there is more competition between the WiMAX networks and the backup networks. Handovers are frequent especially in the worst case conditions. The fluctuating loss rate means video quality never settles in a certain range. These potential fluctuations can be addressed in future work, where factors such as video quality adaptation can be considered. The QAM16 experiences similar quality drops to the QAM64 scenarios and returns a below average video quality for each minute of the simulation.

V. CONCLUSIONS

This paper describes the EMULSIoN, a pluggable, configurable and extensible handover architecture designed to mitigate for environmental conditions for vehicular scenarios. It maintains adequate levels of multimedia quality across different topographical scenarios. It operates by assigning configurable synaptic weights onto network performance metrics. In response to the overall performance experienced on a user's journey, it re-configures these weight allocations to encourage better performance for future journeys over that route. It also further considers the topographic layout over a certain vehicular route and divides it into sub-routes based off of their terrain. Each sub-route is trained with its own set of weights. This defends against sudden shifts in factors such as foliage density and terrain type during the user's journey. Results presented show that EMULSIoN outperforms pre-configured weight approaches in both potential throughput and video quality. Future work will involve further consideration for different weather patterns. This will involve adding a separate neural network to the algorithm that identifies which weather patterns would have detrimental effects on environmental factors and makes temporary weight adjustments to mitigate performance fluctuations. Other work will involve an analysis of how EMULSIoN can support layered video coding (SVC, HEVC) distribution in different vehicular scenarios. Subjective tests will also be done to further highlight EMULSIoN capability in vehicle-based multimedia streaming scenarios.

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