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Abstract - **Recently, the coronavirus pandemic has caused widespread panic around the world. Modern technologies can be used to monitor and control this highly contagious disease. A plausible solution is to equip each patient who is diagnosed with or suspected of having COVID-19 with sensors that can monitor various healthcare and location parameters and report them to the desired facility to control the spread of the disease. However, the simultaneous communication of numerous sensors installed in the majority of an area's population results in a huge burden on existing Long-Term Evolution (LTE) networks. The existing network becomes oversaturated because it has to manage two kinds of traffic in addition to normal traffic (text, voice, and video): healthcare traffic generated by a large number of sensors deployed over a huge population, and extra traffic generated by people contacting their family members via video or voice calls. In pandemics, e-healthcare traffic is critical and should not suffer packet loss or latency due to network overload. In this research, we studied the performance of existing networks under various conditions and predicted the severity of network degradation in an emergency. We proposed and evaluated three schemes (doubling bandwidth, combining LTE-A and LTE-M networks, and request queuing) for ensuring quality of service (QoS) of healthcare sensor (HCS) network traffic without perturbation from routine human-to-human or machine-to-machine communications. Finally, we simulated all proposed schemes and compared them with existing network scenarios. The results have showed that when we have doubled the bandwidth the SCR of all traffic was 100% as same as the Queue strategy. However, when we prioritized the HCS traffic the SCR has recorded 100%, while H2H and M2M traffic has recorded 73%. When we used hybrid network LTE-A and LTE-M network, the HCS and H2H traffic has recorded 100% and M2M traffic has recorded 70%. After analyzing the results, we conclude that our proposed queuing schemes performed well in all conditions and provide the best QoS for HCS traffic.**

Keywords – Internet of Things (IoT), Long-Term Evolution Advanced (LTE-A), e-Healthcare.

I. INTRODUCTION

Throughout modern history, many people have been infected by highly contagious viruses, sometimes resulting in death. These viruses—most recently, the coronavirus—are evolving over time and threatening our lives. The coronavirus has been recorded in 235 countries with 160 million confirmed cases according to the World Health Organization (WHO) (*Coronavirus Disease (COVID-19) - Pandemic*, n.d.). Initially, in December 2019, several instances of possible pneumonia were recorded in Wuhan City of Hubei Province in South China. In January 2020, the Chinese government and the WHO identified the causative infection as a novel coronavirus (SARS-CoV-2) belonging to the same infection group as the severe acute respiratory syndrome (SARS) that broke out in South China in 2002 and 2003. The coronavirus spread quickly across most locales in China after January 17, 2020, leading to more than 7,000 cases by the end of January (Zhong et al., 2020). The incidence continued to increase rapidly until the number of infected persons reached 11,500,302 cases on July 7, 2020. To date, the virus has no specific treatment or cure. Therefore, supportive therapy is considered a primary treatment for this disease to prevent negative effects on patients' health (Song et al., 2020). In this kind of situation, the immediate course of action that has proved most effective is preventing or slowing the spread of disease by restricting the movement and tracking the physical contacts of sick people.

The Internet of Things (IoT) is the technology best suited for monitoring, restricting, and managing infected people (Bajaj et al., n.d.) (Mehmood et al., 2017). The IoT is already involved in every area of life, including home automation, smart meters, e-healthcare, and vehicle-to-vehicle communication. Researchers at Harvard University and Massachusetts Institute of Technology have developed a smart tattoo ink capable of monitoring people's health (Powell & University, n.d.). Many projects have focused on using IoT in healthcare facilities to monitor and control pandemics; however, installing sensors on all suspected and confirmed infected persons generates huge amounts of additional network traffic. In this scenario, healthcare sensor (HCS) traffic may face serious challenges due to its coexistence with human-to-human (H2H) and machine-to-machine (M2M) traffic in terms of delayed access requests, network access latency, and data loss (Chen et al., 2018). Existing networks consist of a huge number of H2H (e.g., video streaming, voice calls, gaming) and M2M (e.g., fire alarm sensors, electricity consumption sensors) transmission requests. Furthermore, adding massive HCS communication requests (e.g., heartbeat, oxygen, and body temperature sensors) may cause network overload and severely degrade the quality of service (QoS) of HCS traffic necessary to save human lives (Chen et al., 2018). Harnessing IoT, given these foreseen network issues, might lead to disaster in the health sector (Chen et al., 2018).

In this paper, we simulate, compare, and analyze various solutions that many authors have proposed for handling the network overload problem. We found that none of these schemes could handle the case of such an emergency (i.e., the pandemic) with existing network capacity. The main contribution of this research article is its development of a new strategy for a queue model that can prioritize the communication of HCS devices (patient monitoring and tracking devices) over H2H and M2M traffic in an emergency scenario such as the coronavirus pandemic. This proposed scheme maintains the QoS of HCS traffic by guaranteeing that H2H and M2M traffic do not affect HCS communication. Finally, we evaluate the proposed scheme using simulations and analyze the results, finding that its performance exceeds that of other systems and addresses the network issues observed in emergency situations, such as network latency, starvation, and overload.

The rest of the paper is organized as follows. Section 2 describes the state of the art. In section 3, we discuss proposed schemes for coping with the network bottleneck problem. Simulation modeling of the enhanced queuing method is provided in section 4, and the results are analyzed in section 5. Finally, a conclusion and suggested directions for future work are presented in section 6.

II. STATE OF THE ART

The IoT is expanding in terms of resources and entering new arenas, including the healthcare and medical fields. E-health technologies and applications, which may include smart healthcare wearable sensors, make the environment of healthcare facilities more flexible. Therefore, a hospital that is well equipped with a wireless sensor network can provide healthcare IoT services (Chen et al., 2018). However, this kind of service needs to collect real-time patient data to monitor and analyze patients' health during their inpatient hospital stays, while they self-quarantine at home, and when they are outpatients moving with care in society.

The nature of the medical field necessitates an early diagnosis and quick treatment or prevention response based on real-time data received from individuals who are diagnosed with, at high risk of developing, or suspected to have a given condition. This kind of service makes high access demands on wireless networks, as every sensor reading that is collected from patients may be critical for that patient's safety and health. In addition, collected data need to be transmitted to the network periodically and in real time without delay or loss in order to prevent mortality. Furthermore, the life of the sensors must be taken into consideration, especially in smart hospital sensor networks. The authors proposed reducing the packet size of transmission links between sensor nodes to decrease the power used in the transmission of data (Chen et al., 2018).

The authors proposed an intelligent diagnosis and treatment assistant program (nCapp) for the COVID-19 virus. nCapp is a software which provides questionnaires that are answered by potential patients (Bai et al., 2020). This kind of assessment helps clinicians identify and isolate individuals suspected of having COVID-19. Therefore, the software assists in preventing the spread of the virus and contributes to the quality control of healthcare services during the COVID-19 pandemic, especially for outpatients.

The authors focused on the importance of implementing mobile health applications or IoT healthcare services using 5G networks due to the capabilities of 5G communication (Ullah et al., 2019). 5G communication can handle a large number of sensor devices; supports long battery life; has enormous bandwidth, high network capability, and very low latency; and is reliable and secure. However, according to the Global System for Mobile Communications Association ('5G Global Launches & Statistics', n.d.), the 5G network will cover only one-third of the world's population by 2025, as 5G infrastructure networks are not fully implemented in most areas. Moreover, the pandemic has further slowed the deployment and implementation of 5G due to the economic crisis and mobility restrictions. In addition, 5G-enabled devices are typically costly or not readily available, and it is often impossible to shift from 4G to 5G technologies in a short period of time. Therefore, more widely used cellular networks such as 4G and LTE need to provide higher bandwidth and low access latency to accommodate HCS devices without major network degradation.

The authors proposed a new model that uses a stability-based *k*-means (SK-means) algorithm to analyze and train the system to predict and diagnose coronavirus patients using data collected from real-time health sensors (e.g., heart rate, body temperature) (Harb et al., 2020). In their study's architecture, the proposed platform consists of four layers:

1. Real-time monitoring of patient health;
2. Real-time decision making and data storage;
3. Patient classification and disease diagnosis; and
4. Data retrieval and visualization.

Moreover, each layer has its own data mining algorithm to find correlations between patients' monitored health and the disease in order to classify and predict infected individuals.

In e-healthcare, the most important task is to keep monitoring and collecting up-to-date data from the patient. However, these body sensors need to send their data after fixed interval of time, in order to keep a track of the patient's health. Therefore, a fog-based monitoring system was proposed to keep monitoring the health of the patients remotely with low costs (Mutlag et al., 2019). In addition, the use of Fog computing has an advantage of having smart gateways and efficient for IoT sensors. Furthermore, the IoT healthcare gadgets such as body temperature, respiratory rate, heartbeat measurement and oxygen meter collect vital signs and sent wirelessly to gateways to the base station of the Healthcare hospitals in order to analyze these data and monitor the health of the patient.

The authors have worked and proposed a solution for handling one request in one time slot, therefore the authors have proposed a methodology for V2V communication not to be affected over H2H and M2M devices using Adaptive eNode-B (Outay et al., 2020). Therefore, their methodology was based on increasing the bandwidth adaptively according to the request needed, until it reaches to its maximum capacity and any additional request after that will be dropped. By that way, they have solved the bandwidth starvation to a certain threshold.

III. PROPOSED ENHANCED QUEUE MODELING FOR HEALTHCARE TRAFFIC

We propose a queue strategy that handles HCS, H2H, and M2M traffic using a priority queue when the system reaches its peak. Requests that are pushed to the queue have a higher priority in the next round of the emergency storm. Originally, the LTE-A network was designed to fulfill and serve the needs of H2H services. However, as machine-type communication (i.e., M2M communication) has been introduced via the IoT and increased in amount, there has been an unprecedented degradation in the performance of LTE-A networks. By 2025, approximately 7.5 billion IoT devices will be added to the system, which is expected to generate $11.1 trillion per year but will massively increase M2M communications (Ikpehai et al., 2019). In light of this current and expected network traffic, experts have focused on developing 5G networks. In addition, the COVID-19 pandemic this year has created more challenges for the healthcare industry. In any future COVID-like situations, there will need to be more HCS devices in order to prevent the spread of the pandemic and avoid putting people in danger. According to Statista (Saeed & Alouini, n.d.), e-healthcare has the potential to achieve $3.3 trillion in revenue by 2025. The addition of a huge number of M2M and HCS devices in the future cannot be achieved without an efficient and reliable network.

In light of this, many researchers have studied the coexistence of H2H, M2M, and HCS communications in LTE-A networks. In this article, we mathematically characterize the key performance features of H2H, M2M, and HCS communications. Additionally, we propose an enhanced queue method using a continuous-time Markov chain (CTMC) model with the following objectives:

- Study the mutual impact of H2H and M2M traffic on HCS communication.
- Measure, analyze, and identify HCS congestion problems.
- Model a new framework called enhanced queue modeling for HCS traffic in the LTE-A network, which is explained in the following sections.

Our system is an M/M/1 queue model with one server, with the arrival of entities following the Poisson process and a service time with an exponential distribution. To evaluate the impact of H2H and M2M transmission in the emergency scenario for healthcare traffic, we assume an LTE-A network using a bandwidth of 1.4 MHz (C = 6 Resource Blocks) in order to maximally stress the system. The following are the parameters used to define the proposed system:

- λ_{M2M} represents the arrival rate of an M2M communication (direct communication between machines over wireless channels).
- λ_{H2H} represents the arrival rate of pure H2H communication (communication between humans through VoIP, file transfer, and so on).
- λ_{HCS} represents the average arrival rate of pure healthcare communications (communication between HCSs and hospital servers or healthcare machines).
- μ_{M2M}, μ_{H2H}, and μ_{HCS} represent the service rate for each technology, respectively.
- λ_{M2M}, λ_{H2H}, and λ_{HCS} represent the average arrival rate of each traffic with the service rate of μ_{M2M}, μ_{H2H}, and μ_{HCS}, respectively.
- H2H and M2M traffic are assigned the same priority while HCS is given the highest.
- A priority queue type is used with a specified capacity size.

In our previous study, we initially received one request per time slot for each type of traffic (M2M and H2H) and observed no limitation problems, as expected. We then began to increase the number of requests (El Fawal et al., 2018). After simultaneously connecting 52,000 devices, the server stopped accepting requests to avoid overload. In this article, we upgrade our previous system. The new proposed system can simultaneously handle two requests per time slot of different types of traffic—including HCS, M2M, and H2H—even in a very saturated state.

The proposed CTMC analytical model consists of four steps:

1. The CTMC model is used as a stochastic process to designate the different states of every possible event for H2H, M2M, and HCS traffic.
2. Equilibrium equations are defined to describe all transition probabilities from one state to another.
3. Equilibrium equations are considered as a linear system.
4. Finally, performance metrics are generated to characterize the performance of H2H, M2M, and HCS traffic in order to evaluate the network.

The network traffic in our system consists of average arrival rates of H2H, M2M, and HCS requests (represented as λ_{H2H}, λ_{M2M}, and λ_{HCS}, respectively). Each incoming request is represented by a state $S(i, j, m, n)$ where i and j represent the number of H2H and M2M requests served, respectively, while $i + j$ represents the ongoing HCS traffic. Similarly, the number of requests waiting in the queue are respectively represented by m, n, and $m + n$ for each type of traffic. The working queuing model or proposed system is shown in Figure 1.

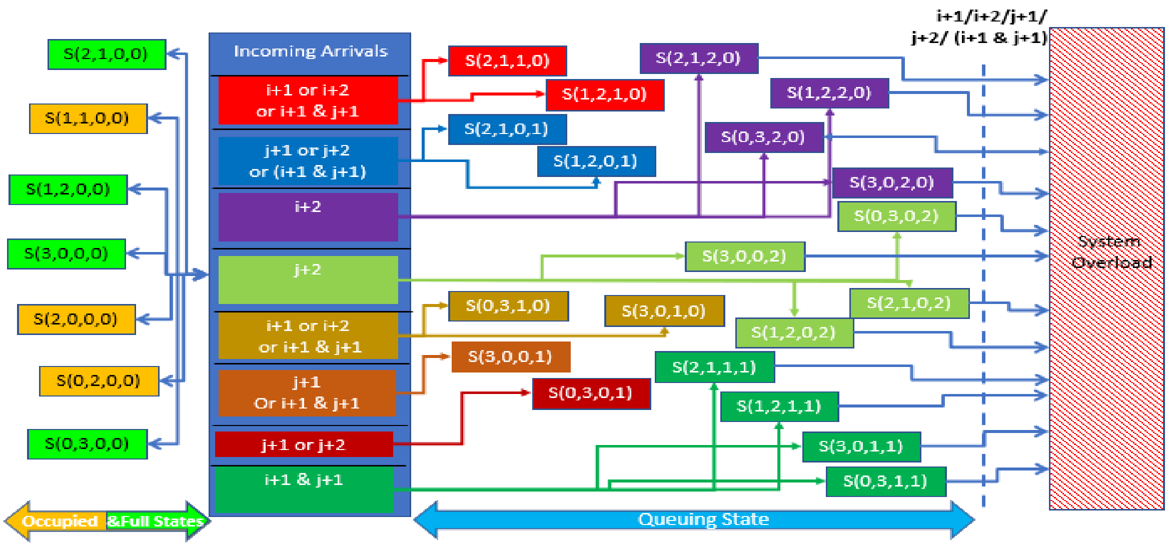

Figure 1: Proposed generic queue model representation for handling two requests per slot

Figure 1 shows how the system handles incoming HCS, H2H, and M2M traffic and pushes such traffic to priority queues until the system reaches maximum capacity. Requests pushed to the queue are assigned higher priority to be served in the next round of the emergency storm. The functioning of the system is explained through an example expressing the states of every request in Figure 2.

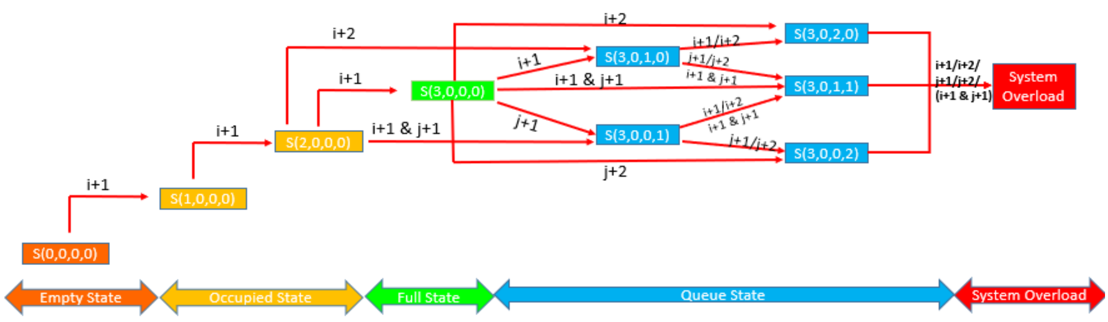

Figure 2: Simple CTMC states being pushed to queue states, where *S* represents a state

When a new request arrives, the system checks whether the LTE-A network is fully reserved. If yes, the request is pushed to the queue; if not, the system allocates a resource block for it. If the queue is empty, then the whole network is reserved for all arrived packets. If it is partially empty, the request will be sent to the network for resource allocation. Ultimately, if the queue becomes full (meaning that the system is full), the request will be rejected until a free resource is available (i.e., there is room in the queue), as shown in the flow chart in Figure 3.

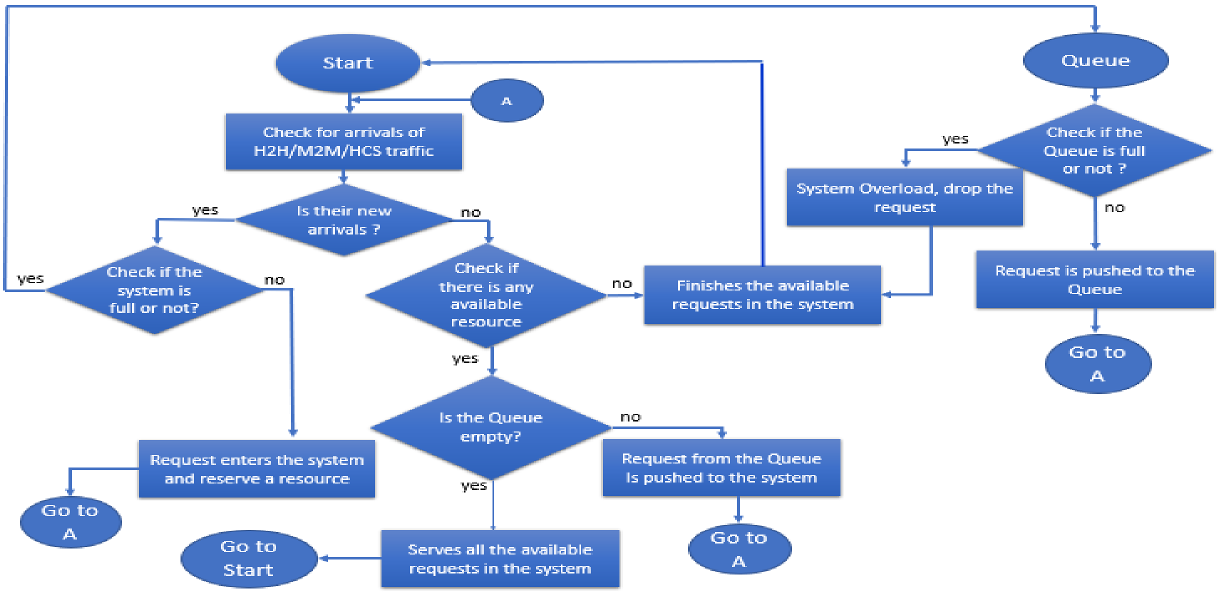

Figure 3: Flow chart of queue model

A. Equilibrium Equations

The equilibrium equations are represented when a new arrival events with an average rate λ and a service rate μ. Thus, the equilibrium equation can be created according to Markov Chain (El Fawal et al., 2018).

The equilibrium equations for each state (empty, occupied, full, and queue) of the serving queue are as follows:

1. Empty State:

$$(2\lambda_1 + 2\lambda_2 + (\lambda_3) * \Pi\,(0,0,0,0) = (\mu_1 * \Pi\,(1,0,0,0)) + (\mu_2 * \Pi(0,1,0,0)) + (\mu_1 * \Pi(2,0,0,0)) + (\mu_2 * \Pi(0,2,0,0)) + ((\mu_3) * \Pi(1,1,0,0))$$

2. Occupied State:

$$(\lambda_1 * \Pi(0,0,0,0)) + (\mu_1 * \Pi(2,0,0,0)) + (\mu_2 * \Pi(1,1,0,0)) + (\mu_1 * \Pi(3,0,0,0)) + (\mu_2 * \Pi(1,2,0,0)) + ((\mu_3) * \Pi(2,1,0,0)) = (2\lambda_1 + 2\lambda_2 + (\lambda_3) + \mu_1) * \Pi(1,0,0,0)$$

3. Full State:

$$(\lambda_1 * \Pi(0,2,0,0)) + (\lambda_2 * \Pi(1,1,0,0)) + (\lambda_2 * \Pi(1,0,0,0)) + ((\lambda_3) * \Pi(0,1,0,0) + \mu_2 * \Pi(1,2,0,1) + \mu_1 * \Pi(1,2,1,0) + \mu_1 * \Pi(1,2,2,0) + \mu_2 * \Pi(1,2,0,2) + \mu_3 * \Pi(1,2,1,1)) = ((\mu_1 + 2\mu_2 + (\mu_3) + 2\lambda_1 + 2\lambda_2 + \lambda_3) * \Pi(1,2,0,0))$$

4. Queue State:

$\lambda_1 * \Pi(1,2,0,0) + \lambda_3 * \Pi(1,1,0,0) + \lambda_1 * \Pi(0,2,0,0) = (2\mu_1 + \mu_3) * \Pi(1,2,1,0)$

where λ_1, λ_2, and λ_3 represent the respective average arrival rates for M2M, H2H, and HCS traffic; μ_1, μ_2, and μ_3 represent their respective average service rates; and Π represents the probability of every state.

As described above, *i, j, m,* and *n* denote the number of ongoing services of H2H, M2M, and HCS traffic. The system moves from one state to another when a service is achieved or a new request arrives (by increasing or decreasing *i* or *j*) with a steady-state probability $\pi(i, j)$. We can derive a linear equation as follows:

$$\sum_{i=0}^{C} \sum_{j=0}^{C-1} \pi(i,j) = 1, 0 \leq \pi(i,j) \leq 1 \tag{1}$$

The steady-state probability vector π is represented in a square matrix as:

$$\pi = \begin{pmatrix} \pi(0,0) \\ \pi(0,1) \\ \cdot \\ \cdot \\ \pi(c,0) \end{pmatrix} \tag{2}$$

where C represents the number of resource blocks.

B. Service Completion Rate

To validate our model, the equations has been introduced into square matrix and the code has been generated, therefore the service completion rate (SCR) is calculated as:

$$SCR = \sum_{i,j} i\mu\pi(i,j) \tag{3}$$

After solving the above linear system and introducing them into MATLAB which has been developed as per equation (1), we can calculate and evaluate the SCR of the generated equation equilibrium as per equation (3) and validates our mathematical model by Simulation model.

C. Validating Our Model with Mathematical Equations

In order to validate our Simulink model, we proved our model mathematically using Markov Chain. Therefore, in order to make this test easier and simpler, we are going to assume that arrival rate for M2M is equal to 4 (λM2M =4), an arrival rate for HCS equal to 4 (λHCS =4) and an arrival for H2H equal to 4 (λH2H =4) , with C=6 and their service rate equal to 1 (μH2H= 1, μM2M = 1 μHCS = 1).

Therefore, the results of the MATLAB code, as we mentioned earlier has been introduced into a matrix after the equation equilibrium has been generated using Markov Chain, is as follow:

SCR_M2M = 100%, SCR_H2H= 50% and SCR_HCS= 0%

Since, in MATLAB we can't set up priority, system has taken the procedure as First Input First Output (FIFO). Therefore, in Simulink we are going to give same parameters and give the highest priority for M2M, then H2H and finally HCS traffic and the result is shown in Figure 4.

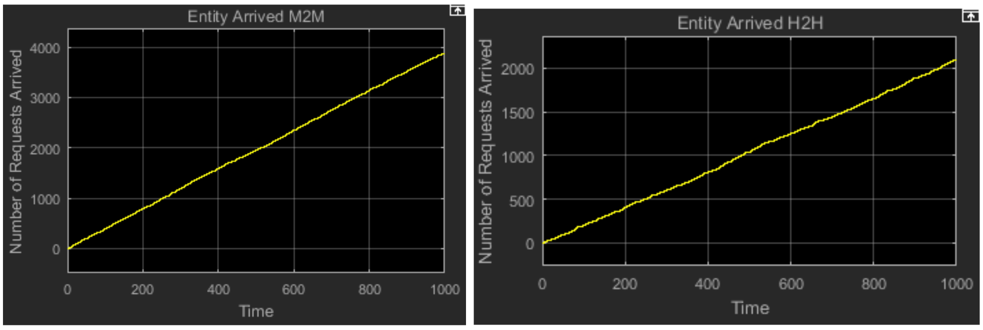

Figure 4: Entity Arrived of H2H and M2M for Validation Scenario

According to the results shown in Figure 4, the number of devices departed from H2H is 4000 (λH2H =4) and only 2000 has been arrived, whereas the number for devices departed from M2M is 4000 (λM2M =4) and 4000 has been arrived. Therefore, we can conclude that, our system is working properly and it is validated.

So, now in order to analyze the impact of H2H and M2M over HCS traffics, we are going to simulate different scenarios.

IV. NETWORK SIMULATION FOR PERFORMANCE ANALYSIS

The proposed system was evaluated using a simulation study. Different models were created using Markov chain methods to describe system variation. The OMNeT++ framework and MATLAB Simulink environment were used to create different simulation scenarios. For each scenario, different simulation runs were developed to test each possible network situation. Four simulation scenarios were created to represent four types of network settings:

1. Existing network;
2. Network upgraded by doubling bandwidth;
3. Combination of LTE-A and LTE-M networks; and
4. Network with proposed queuing scheme.

The performance of each network model was evaluated in both normal and emergency conditions. Different simulation runs were created for each network model as follows:

1. Less populated area;
2. Highly populated area;
3. Low-frequency emergency situation (λ_{HCS} = 1 request);
4. Moderate-frequency emergency situation (λ_{HCS} = 4 requests); and
5. High-frequency emergency situation (λ_{HCS} = 13 requests).

A hierarchical representation of simulation runs is shown in Figure 5.

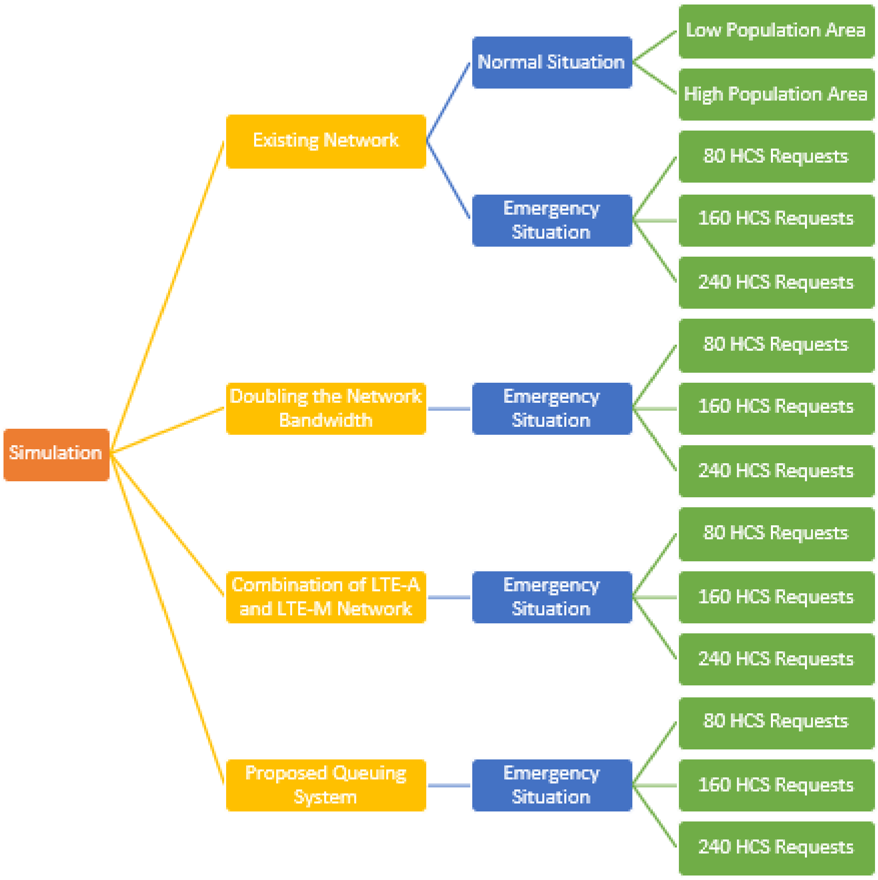

Figure 5: Simulation models

We developed a city communication network in OMNeT++ where we generated H2H, M2M, and HCS traffic routed through different servers, as shown in Figure 6.

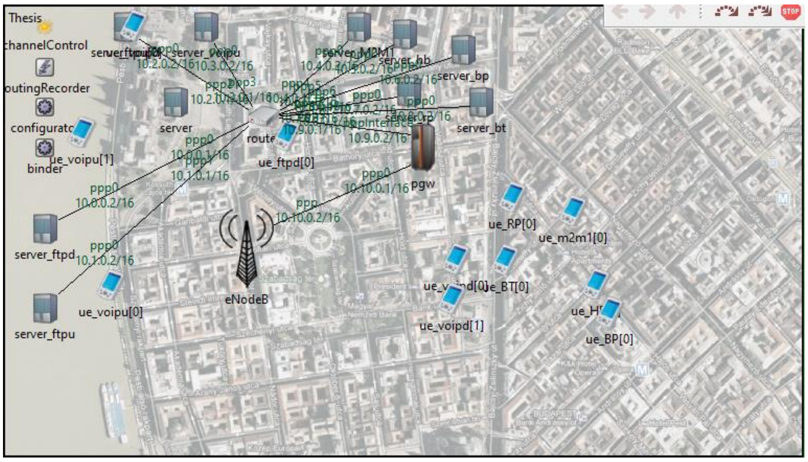

Figure 6: SimuLTE scenario representing LTE-A network

Using the network generated in OMNeT++, we designed many scenarios, shown in Figure 4, to evaluate the performance of the LTE-A network when handling different types of traffic as well as the impact of HCS traffic on H2H and M2M transmission and vice versa. The SimuLTE parameters for the LTE-A network settings are shown in Table 1.

TABLE 1: SIMULATION PARAMETERS

Parameter	Value
Simulation length	200 s
Terminal velocity	120 km/s
Mobility type	Linear mobility
Transmission bandwidth	1.4 MHz (for download and upload each)
Number of PRBs	6 (for download and upload each)

A. Simulation Model of Existing Network

We evaluated the performance of the existing network under different conditions, including normal versus emergency conditions and less populated versus highly populated areas. First, the performance of the server was observed by setting H2H traffic at the highest priority and M2M and HCS at the same priority, with the following parameters:

- An arrival rate of H2H requests such that $\lambda_{H2H} = 1$;
- An arrival rate of M2M requests such that $\lambda_{M2M} = 1$;
- An arrival rate of HCS requests such that $\lambda_{HCS} = 2$; while
- $\mu_{H2H} = 0.5$, $\mu_{M2M} = 1$, and $\mu_{HCS} = 1$.

Simulation was conducted in Simulink. The results of at least three runs were averaged to calculate the SCR of the system, and traffic was analyzed.

The results show that all traffic was fully served in the LTE-A network with bandwidth 1.4 MHz and six PRBs. These results show that the system is working normally, since the devices only occupied an average of five out of six resources. Since H2H traffic is generated with an arrival rate of $\mu_{H2H} = 0.5$, it reserves one out of six resources in total for two consecutive intervals of time. This means that the system does not suffer from any overload. Hence, the server utilization index of the system is:

SUI = (sum of the number of arrival rate / total number of resource blocks) = 0.83

The observed server utilization of the system is approximately 80%, which means that the system is relaxed and working freely without any congestion. We tested this model for both highly inhabited areas and less inhabited areas and found it to work well in both. The results are shown in Figures 7 and 8.

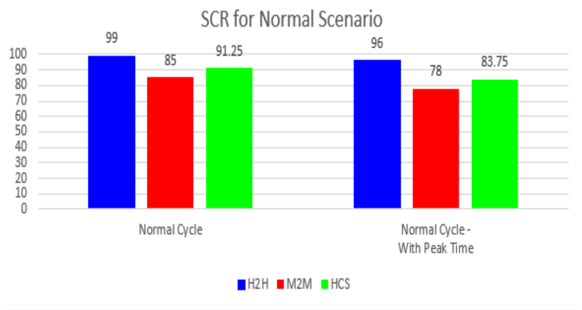

Figure 7: Performance of existing network in less inhabited areas

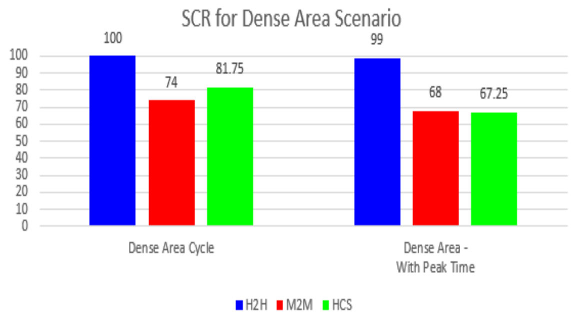

Figure 8: Performance of existing network in highly inhabited areas

B. Simulation Model of Existing Network in Emergency Conditions

We also evaluated the functioning of the existing network in emergency conditions. In an emergency scenario, the number of e-HCSs is expected to increase enormously. In this situation, we focused on analyzing and observing the performance of the LTE-A network for patient devices (e.g., heartbeat, blood pressure, respiratory, and body temperature sensors). We considered three parameters for the emergency scenario, as follows:

1. The emergency scenario considered 20 H2H users (including VoIP-DL and VoIP-UL), 10 M2M users, and 80 HCSs (including heartbeat, body temperature, and respiratory sensors) with six PRBs.
2. The emergency scenario with moderate traffic load time considered 20 H2H users (including VoIP-DL and VoIP-UL), 10 M2M users, and 160 HCSs (including heartbeat, body temperature, and respiratory sensors) with six PRBs.
3. The emergency scenario with full peak time considered 20 H2H users (including VoIP-DL and VoIP-UL), 10 M2M users, and 240 HCSs (including heartbeat, body temperature, and respiratory sensors) with six PRBs.

After simulating the above cases, the results showed that the H2H traffic revealed no changes. The VoIP traffic has a higher priority than M2M and e-health traffic when accessing the network in normal situations. Moreover, as the number of e-HCSs increases, M2M devices suffer from performance degradation due to their low priority.

However, e-HCSs suffer from severe performance degradation due to the overload of the LTE-A network caused by the huge number of devices attempting to access the network as well as bandwidth starvation, as shown in Figure 9. Moreover, as shown in Figure 9, M2M performance maintained the same level but HCS dropped by up to 48%—an unacceptable level, given that it is a matter of human life.

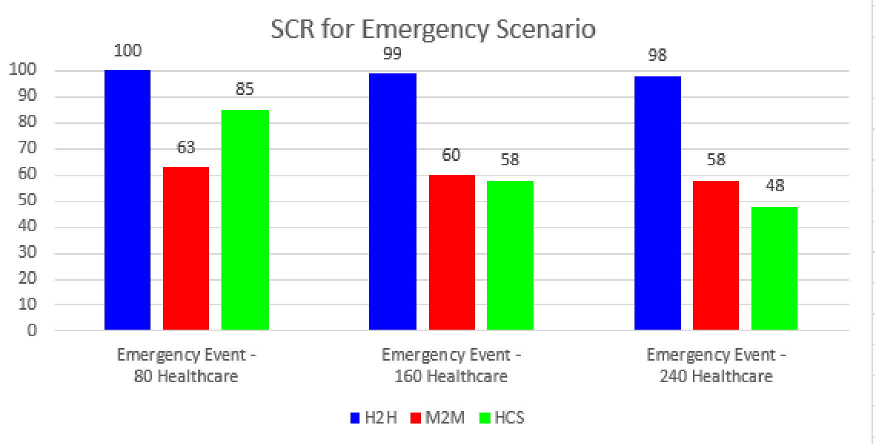

Figure 9: Performance of existing network under varying emergency conditions

The extreme emergency scenario was tested by increasing the number of HCS devices to as much as 13,000. We observed that the SCR of HCS and M2M traffic dropped to 20% while H2H communication maintained its QoS at the cost of HCS and M2M service. This is not acceptable, especially when fighting a pandemic like COVID-19.

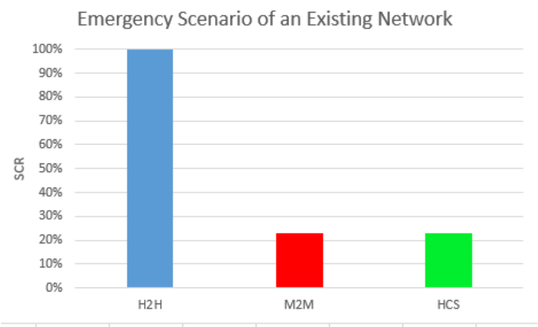

Figure 10: Simulation model of existing network under extreme emergency conditions

C. Simulation Model of Existing Network Upgraded by Doubling Bandwidth

In this model, we evaluated the functioning of an upgraded existing network. The network was upgraded by increasing the bandwidth by 400% to analyze how it would cope with this emergency situation.

In this simulation case, all the parameters were the same as in the previous emergency scenario but with 25 PRBs to solve the congestion issue. The LTE-A network showed improved performance in handling e-HCSs, as shown in Figure 9. The results of the SCR show that the H2H traffic maintained 100% performance due to its high priority level, whereas the SCR of e-HCSs improved until it reached approximately 80% as the number of e-HCSs increased (in contrast to 48% with six PRBs). This means that e-HCSs suffered from neither access delay nor overload. The results are shown in Figure 11.

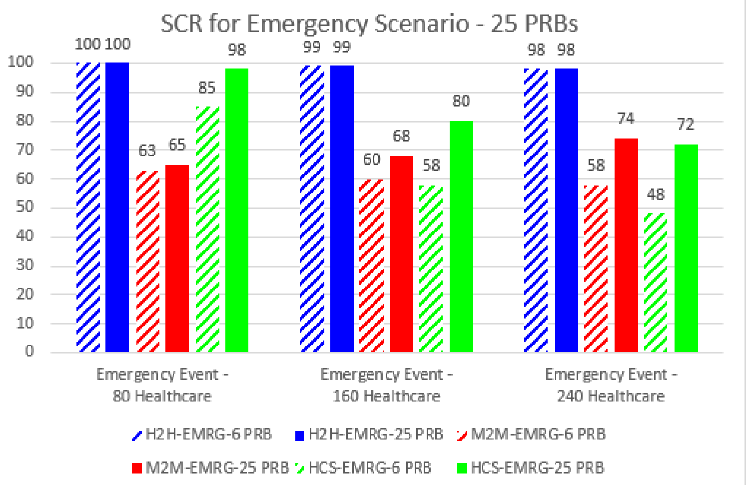

Figure 11: Performance of upgraded existing network under emergency conditions

D. Simulation Model of Combined LTE-A and LTE-M Network

In this simulation run, we tested the performance of a network system with coexisting LTE-A and LTE-M networks in order to solve the overload and access delay problems. In this simulation, we assigned H2H traffic to the LTE-A network and M2M and e-healthcare traffic to the LTE-M network. This ensured that the high priority of H2H traffic while accessing the network would not affect the performance of e-healthcare traffic, as shown in **Figure 12: SCR for emergency scenario with LTE-A and LTE-M network**Figure 12. The results show that e-HCSs performance is improved until it reaches around 70% as the number of e-HCSs increases. This means that H2H traffic does not affect e-healthcare traffic when accessing the network.

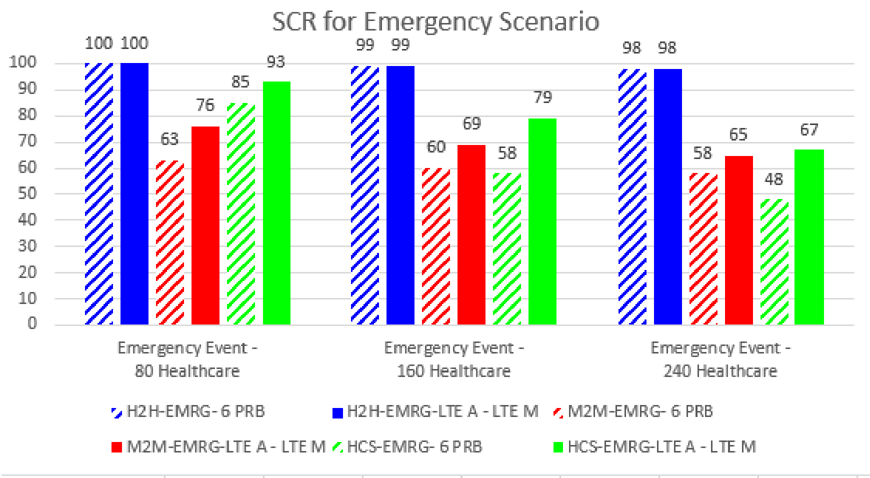

Figure 12: SCR for emergency scenario with LTE-A and LTE-M networks

E. Simulation Model for Proposed Queuing Scheme

In this scenario, we gave the highest priority to queue traffic, followed by HCS traffic with the second-highest priority and finally H2H and M2M traffic with the joint third-highest priority. We assume that we have two waves of normal traffic, with a queue capacity of five.

1. First Storm for Emergency Scenario Using Queue Strategy

We assigned the highest priority to queue traffic, followed by HCS traffic with the second-highest priority and similar priorities for H2H and M2M traffic. We assumed two waves for normal traffic, with a queue capacity of five. In the first wave, the queue was set at zero, since initially the queue is empty. Traffic was generated for the simulation according to the following parameters:

- An arrival rate of H2H requests such that $\lambda_{H2H} = 1$;
- An arrival rate of M2M requests such that $\lambda_{M2M} = 2$;
- An arrival rate of HCS requests such that $\lambda_{HCS} = 4$;
- An arrival rate of queue requests such that $\lambda_{Queue} = 0$; while
- $\mu_{H2H} = 0.5$, $\mu_{M2M} = 1$, $\mu_{HCS} = 1$, and $\mu_{Queue} = 1$.

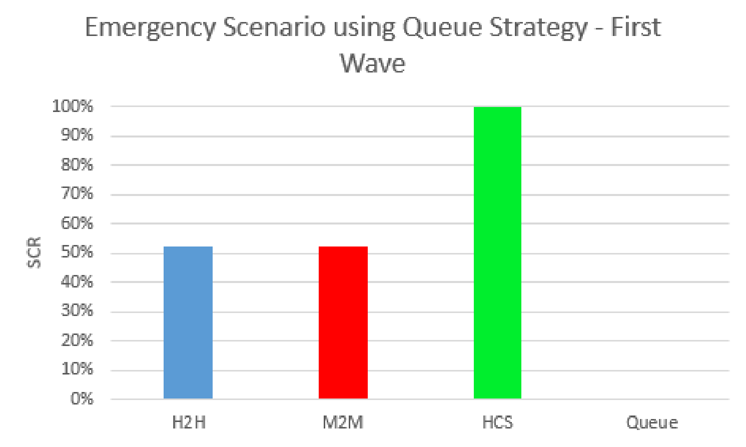

Figure 13: SCR of an emergency scenario using queue strategy (first storm wave)

According to the results shown in Figure 13, HCS traffic with the highest priority was fully served in the LTE-A network with six PRBs, while the remaining bandwidth was divided between H2H and M2M traffic since they shared the same priority level. Moreover, as can be seen in the queue, 1,430 arrivals from H2H and M2M traffic were pushed to the queue.

2. *Second Storm for Emergency Scenario Using Queue Strategy*

In the second wave, we assumed that, after one minute, a new wave or storm of emergency traffic had arrived per the following parameters:

- An arrival rate of H2H requests such that $\lambda_{H2H} = 1$;
- An arrival rate of M2M requests such that $\lambda_{M2M} = 1$;
- An arrival rate of HCS requests such that $\lambda_{HCS} = 3$;
- An arrival rate of queue requests such that $\lambda_{Queue} = 1.43$; while
- $\mu_{H2H} = 0.5$, $\mu_{M2M} = 1$, $\mu_{HCS} = 1$, and $\mu_{Queue} = 1$.

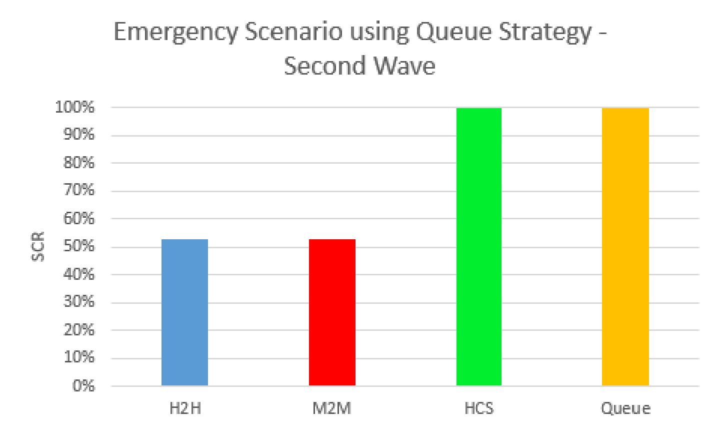

Figure 14: SCR of an emergency scenario using queue strategy (second storm wave)

Figure 14 shows the results of the second storm wave. The highest priority was given to the queue in order to complete the arriving traffic that was pushed to the queue in the first wave of the storm. The second-highest priority was assigned to HCS traffic, while H2H and M2M traffic had the same priority level. The SCR of the queue traffic was 100%, and since the queue traffic was from the previous storm (in this case, H2H and M2M traffic), we increased the SCR for H2H and M2M from 52% to 100% (from the previous wave).

Moreover, the overall delay time for a request in the queue was 0.05 ms (50/1000). The authors found that according to UCA OpenSG specifications, the maximum acceptable delay latency for a delay-tolerant application is 60 s, for an average payload of 1.2 kB and an arrival rate of six messages per day per device (Kumar et al., 2016). However, the acceptable delay latency for a delay-sensitive application is less than 3 s, which represents a payload of less than 25 B and an arrival rate of 96 messages per day per device. Therefore, our delay latency is acceptable for both a delay-tolerant request and a delay-sensitive application, since our requests are delayed for only 0.05 ms in order to be served in the second wave of the storm.

Furthermore, when we doubled the bandwidth, the SCR of all traffic was 100% SCR, the same as when we used the queue strategy. However, when we prioritized HCS traffic over all other traffics in such an emergency event, HCS traffic recorded 100%, while H2H and M2M recorded 73%. When we used an LTE-A and LTE-M hybrid network, HCS and H2H traffic recorded 100% while M2M traffic recorded 70%. In summary, all results showed an improvement in the performance of the network and in QoS. However, the best results were achieved when we doubled the bandwidth and used queue modeling, since the SCR maintained 100% and the QoS of H2H, M2M, and HCS traffic was not affected at all. On the other hand, doubling the bandwidth is not the optimal solution, since it is costlier for the government to increase the bandwidth in every LTE-A network. Using a queue strategy is more efficient and less expensive, as shown in Figure 15.

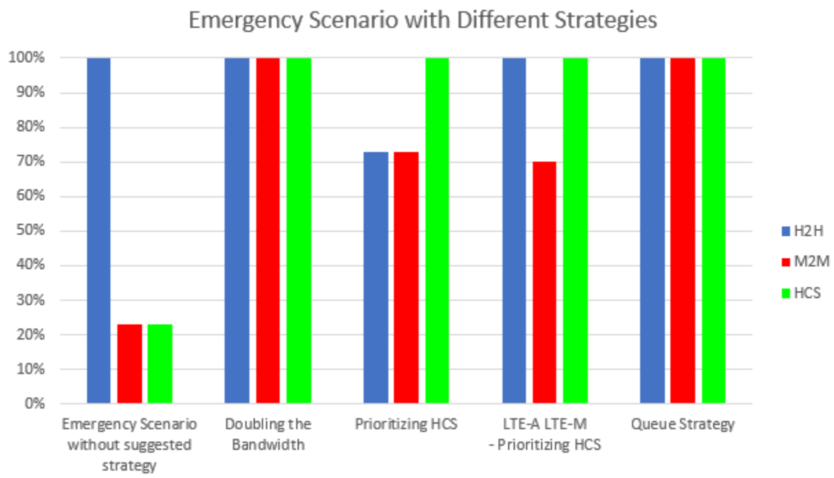

Figure 15: Emergency scenario with different strategies

V. CONCLUSION AND FUTURE WORK

In this area, many researchers have focused on addressing the coexistence of H2H and M2M devices over LTE networks and the challenges faced by M2M devices. Authors have proposed many solutions to this problem, such as giving priority to H2H and M2M traffic or using the LTE-A and LTE-M networks for H2H and M2M traffic, respectively. Others have worked on finding a solution to the bandwidth starvation problem. In our study, we improved the network to fulfill the needs of HCS devices in order to keep track of the health of people infected with a contagious disease. In addition, we proposed more than one suitable solution for the network overload and bandwidth starvation problems. The optimal solution was found when we maintained the QoS of all traffic and fulfilled our main target: to fulfill all HCS traffic in an emergency event without letting H2H and M2M traffic impact it. In future work, we plan to assign different priorities in the queue for emergency events so that the HCS traffic pushed to the queue will be served first in the next storm, before the H2H and M2M requests in the queue. Furthermore, we can imagine a system with multiple queues where each queue is reserved for one type of traffic instead of sharing the same queue. This way, the QoS of each traffic type will not be affected in the event of a huge number of devices accessing the network.

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