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# Predictive Health Monitoring of Multimorbidity: A Simulation Experiment Using OPNET Modeller

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***Abstract— Primary health care services are increasingly at the heart of integrated people-centred. They provide an entry point into the health system, ongoing care coordination and a person focused approach. Patient safety incidents involve active events, such as adverse drug events, intervention complications, infections and care failures, prescribing and delayed diagnosis. As a result, patients with multimorbidity are at higher risk of safety issues. In this study, monitoring is conducted on data streams from wearable body sensors enabled by Healthcare Internet of Things, overlapping time series plotting of body parameters, and a rules-based decision engine with artificial intelligence capabilities to detect risky patterns of variations in the body parameters. This research investigates a possible design for predictive health monitoring of multimorbidity that individual hospitals can implement at low costs and high operations effectiveness and feasibility. This research was conducted in OPNET modeller to: (a) Conduct simulation-based testing of a low-level Healthcare 4.0 design for monitoring of multimorbidity; (b) Suggest practical design, operational details, and limitations for predictive health monitoring of multimorbidity. The design details were captured from literature and the simulated design was created for monitoring 105 health sensors by a single hospital in its vicinity of 10 Kilometers radius. The design comprised of edge computing servers in the hospital's premises connected to a fog computing system for running body area networks of body-attached sensors of 100 individuals. The connections between the edge computing servers and the fog computing system were 100 Mbps broadband Internet connections on Optical Fiber. The simulation was conducted to study effects of mobility of the citizens, effects of TCP session and transmission delays, effects of buffering in the WLAN routers, and effects of TCP congestion windows. The simulation pattern was defined by an operations algorithm designed with the help of technical literature review. The WLAN routers should have high capacity of buffer memories to temporarily store health data streams and large number of receiving channels to avoid information losses. The TCP session timeouts and congestions can be very harmful for individuals being monitored critically. Hence, bandwidth allocation to body area networks should be planned based on the frequency and amount of data needed by the hospitals. The body area networks deployed on individuals should have carefully conducted right sizing of number of parameters, their data volumes, transmission frequencies, and criticality of the individuals. The hospitals should classify patients in different classes based on criticality, data volumes, and frequencies of monitoring needed, and allocate appropriate multi-tiered body area networks for the different patient classes. A one size fit for all approach will fail.***

***Keywords— Healthcare 4.0, multimorbidity, OPNET, wearable body sensors, Healthcare Edge/Fog Computing***

## I. INTRODUCTION

Edge computing and cloud computing based data consolidation of the monitored cases can help in widening the scope of monitoring of elderly and vulnerable citizens based on patterns analysis instead of the current practice of case-by-case analysis [2]. The data collection can be done using body wearable sensors powered by Healthcare Internet of Things (HIoT) [1]. The sensors can be designed to collect time series data about critical health parameters, similar to the continuous monitoring systems used in an intensive care unit (ICU). The data can be consolidated for continuous monitoring and analysis such that interventions or hospital admissions can be initiated through collaborated healthcare processes and teamwork when the data suggests the needs ([3], [4]). These new technology enhancements are viewed as the new revolution in healthcare called the Healthcare 4.0 [5]. Given the value it proposes for remote and predictive healthcare, it can be of value to provide effective and low cost services to the elderly and vulnerable citizens. This research investigates the technical design of Healthcare 4.0 for remote and predictive health monitoring of the citizens of elderly and vulnerable citizens in Kenya.

## II. PURPOSE

To simulate a practical design based on Healthcare 4.0 towards predictive health monitoring of Multimorbidity.

## III. OBJECTIVES

This research was to:

1) Conduct simulation-based testing of a low-level Healthcare 4.0 design for monitoring of elderly and vulnerable citizens
2) Suggest practical design, operational details, and limitations for predictive health monitoring of elderly and vulnerable citizens

The research questions investigated are the following:

1) What may be an appropriate design for predictive health monitoring of elderly and vulnerability citizens in the vicinity of a hospital in Kenya?
2) What may be the design, operational details, and limitations of predictive health monitoring of elderly and vulnerable citizens in the nation of Kenya?

The highlights of the research are the following:

1) A design suitable for predictive health monitoring of 100 individuals in the vicinity of a hospital within ten kilometers radius by installing and operating hospital-owned edge computing servers, a wireless local area networking, and body area networking of sensors attached to the bodies of individuals monitored.
2) Simulation of the design in a professionally accredited simulation tool (OPNET).
3) Recommendations on design, operational details, and limitations of predictive health monitoring of elderly and vulnerable citizens in the nation of Kenya.
4) Several observations and their interpretations of the predictive healthcare design and simulations useful for academic research in future.

## IV. LITERATURE REVIEW ON PREDICTIVE HEALTH MONITORING

Medical electronics equipment for measurements, tests, and continuous monitoring have advanced to such a state that signals of anomalies hidden in biological, chemical, and physical indicators of almost all the human diseases can be captured and stored as (Electronic Health Records) to diagnose the health state of an individual accurately ([6], [7], [8], [9]). Massive scale data is being collected such equipment but have not been analyzed for making predictions about future health anomalies in patients. The earlier challenges were in lack of data consolidation and integration, and lack of sophisticated models for data analytics. These gaps can be now bridged in the evolution of Healthcare 4.0 framework of technologies and systems. With the evolution of HIoT, big data analytics and machine learning, electronic health records can be collected in real time and stored in big data systems for predictive analytics. Figure 1 shows a simple layout of the process flow for predictive analytics in healthcare [8]:

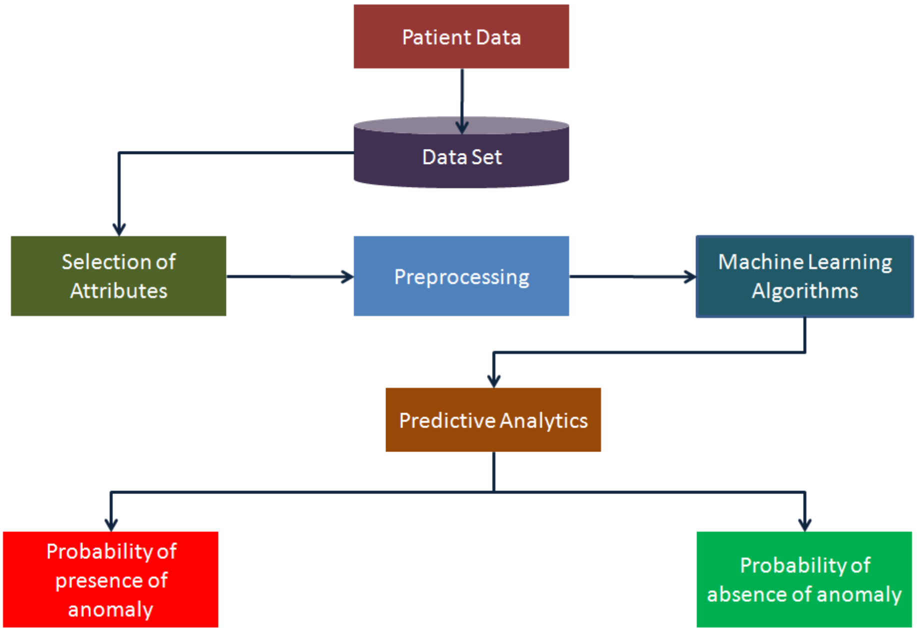


Fig. 1 A Predictive Analytics flow [8]

The patient data collected in raw format from their body sensors enters the big database in unstructured manner ([7], [8]). The data is queried using a selection of attributes of interest, pre-processed, and then applied to machine learning for interpretation and analytics. In deep learning, the machine learning data is trained using historical electronic patient records to build perceptions of knowledge at the machine level. This process is called supervisory learning. The supervisory learning shall require domain-based constructs of data using in-depth knowledge of healthcare. For example, an algorithm can be designed to predict probability of heart diseases.

The real time data collected from the patients is used as testing data to make predictions ([7], [8]). The sensory data collected about medical conditions of patients is not limited to body sensors only [9]. They can comprise of other forms of sensors such as indoor environmental sensors, ambient sensors, cameras, microphones, microbial sensors, and hygiene sensors. The data collected needs to be pre-processed to match it with the training data used to train the deep machine learning algorithm. The machine learning architecture can be in the form of convolutional neural networks for learning from images and patterns, and in the form of recurrent neural networks for learning from data streams ([10], [9]). The results may be in the form of status updates to monitoring doctors, emergency alerts, or alarms for immediate intervention. Several service scenarios can be designed for predictive healthcare for elderly and vulnerable people, such as prevention of diabetes, preventive emotional support, prevention of stroke, cancer, HIV, and heart diseases, reduction of obesity, rehabilitation of stroke, preventive sepsis detection, and prevention of suicidal tendencies. These scenarios are possible under healthcare 4.0, which requires a larger national investment as discussed in the literature review of Healthcare 4.0 in the next section.

## V. HEALTHCARE 4.0

A layout of the Healthcare 4.0 framework showing its essential components is presented in the Figure 2 [5]. As evident in the Figure 2, Healthcare 4.0 needs to be implemented through commitment and participation of the national government supported by policies, regulations, political commitments, national medical institutions, and nationwide medical administrators. A National Healthcare System is needed to govern the nationwide network of hospitals integrated with the national medical supply chain, insurance and payment systems, doctors, nurses, and medical staff, and the Healthcare 4.0 system of mHealth Apps, national patient monitoring and health tracking system, patient big databases, and the deep machine learning. The National Healthcare System should adopt the Healthcare 4.0 framework to be able to deliver predictive healthcare ubiquitously to all the citizens of the country, and be governed by the national authorities and the government.

 

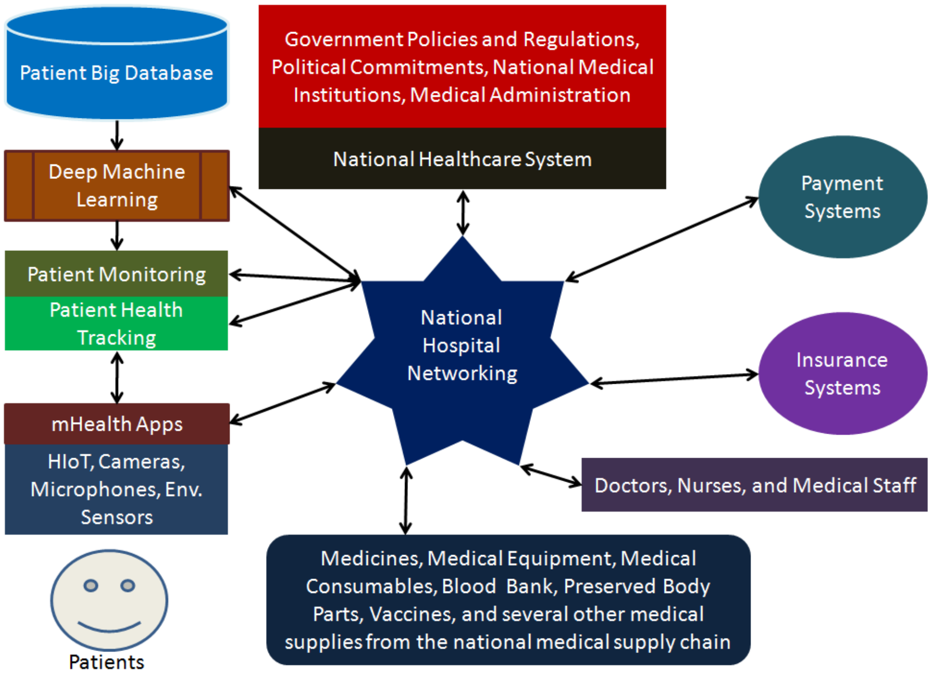


Fig. 2 The Healthcare 4.0 framework (simplified diagram [5])

The knowledge gained from the literature review was applied to develop the proposed architecture for predictive health monitoring of elderly and vulnerable citizens in the nation of Kenya. The details are presented in the next section.

## VI. RESEARCH METHODOLOGY

The research methodology used for this research was designing the architecture for predictive health monitoring and modelling its operational algorithm in a network simulator called OPNET. Simulations were conducted for a scenario of 100 mobile apps communicating with a fog computing infrastructure deployed for remote predictive health monitoring. The design followed for modelling and simulations is presented in Figure 3. The sensors are shown as generic data collection units, which may be body sensors, cameras, microphones, motion sensors, environmental sensors, or any other sensory equipment innovated under Healthcare 4.0.

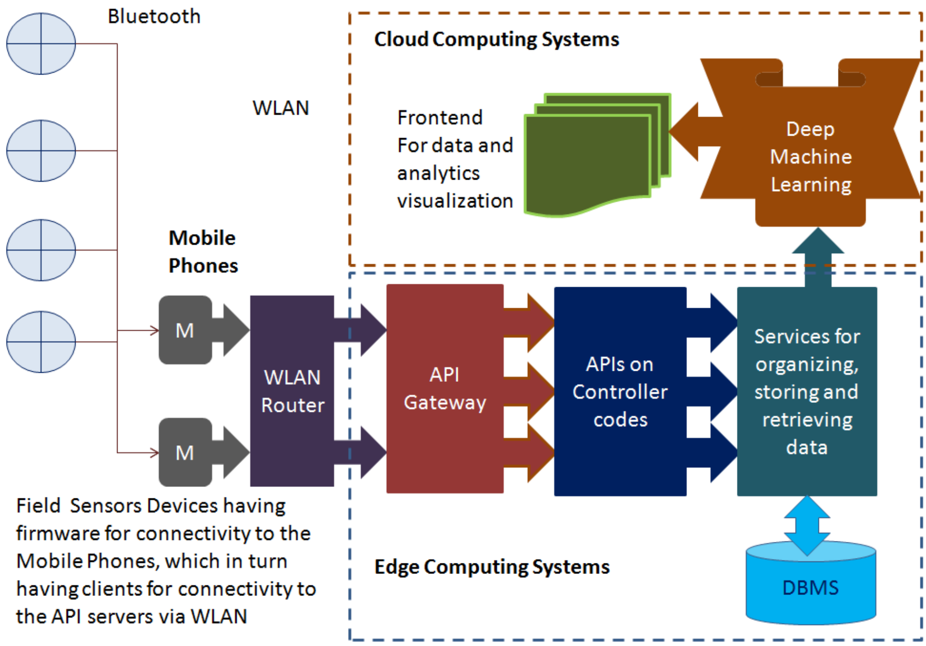


Fig. 3 The Proposed architecture for predictive health monitoring of elderly and vulnerable citizens in Kenya (author's proposed design)

 

The All sensors are assumed to be having the required firmware to connect with mobile phones using Bluetooth connectivity. The mobile phones shall act as routers for the sensors as well as hosts for mHealth apps standardised by the government under the nationwide Healthcare 4.0 framework. The mobile phones are configured to connect to local WLAN access points deployed by the government for access to healthcare edge computing systems. The national healthcare network can be split into two systems: fog/edge computing and cloud computing [5]. The edge computing system shall be formed by a network of hospitals in the country, and the cloud computing system is proposed to host the deep machine learning and the front end for data and its analytics visualisation accessible ubiquitously to all the doctors, nurses, and healthcare workers in the country. In this research, the fog/edge computing part of Healthcare 4.0 is modelled, as shown in Figure 4. The model is designed to operate the algorithm phases shown in Figure 5, which has a mix of co0ncurrent and serial interactions. The full algorithm realisation was modelled using destination configurations of all the devices shown in Figure 4.

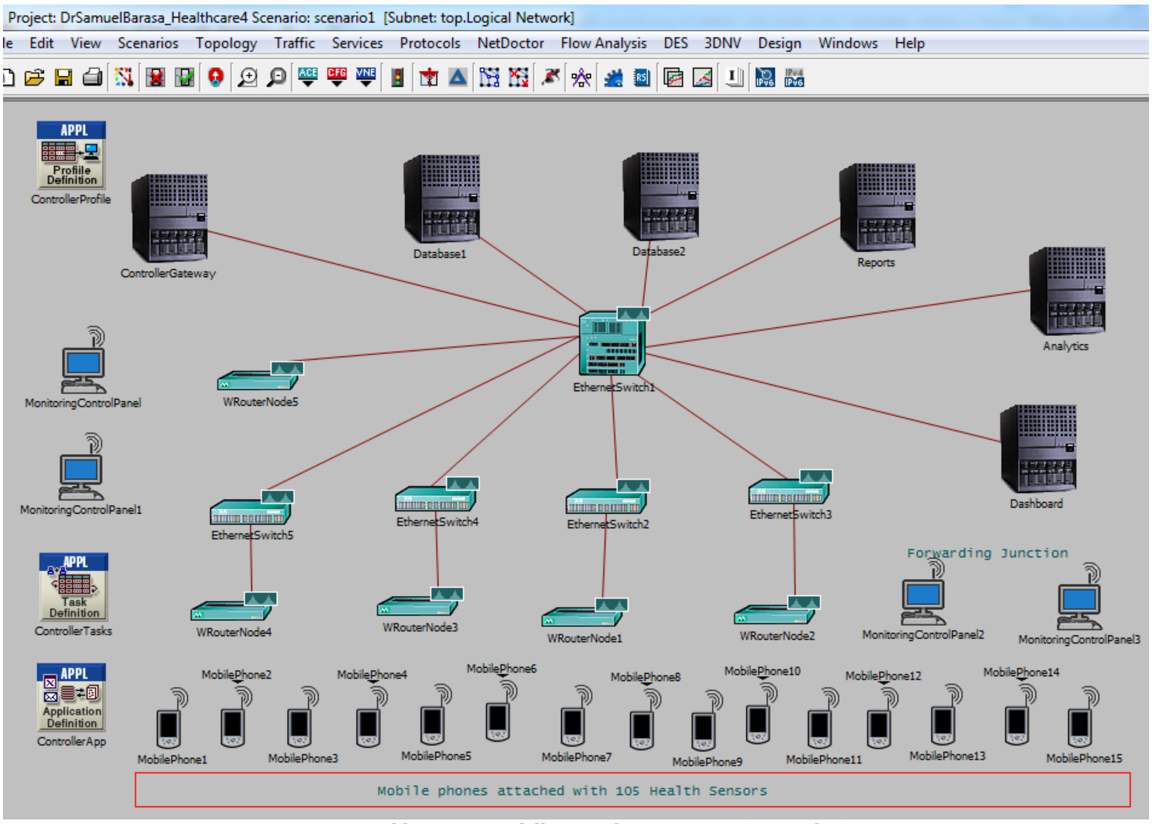

Fig. 4 Healthcare 4.0 modelling at edge computing (Screenshot)

The model is created as an edge computing infrastructure similar to a local Internet Service Provider (ISP) offering fibre-to-home Internet services to customers. Such ISPs offer deployment of a local Wi-Fi router at the customer's premises having optical fibre interface connected to a last mile cable. The premise of the customer is networked wirelessly such that all laptops and desktops can be connected to the Internet. The network modelled shown in Figure 4 has similar network architecture but with different specifications. The mobile phones are used as local hosts of health apps connecting up to seven health sensor devices over Bluetooth. The apps are pointed to API gateway that routes the traffic to API controllers for data collection and consolidation. In Figure 4, the server named "ControllerGateway" is modelled as host for the API gateway as well as the API controller codes. The data is stored in two database servers named as "Database1" and "Database2". The backend application used by the doctors and healthcare staff has three components for reporting, analytics, and dashboard running on designated servers of same name. All the servers are connected to a core switch, and the Wi-Fi routers at customers' ends are connected to edge switches. The phases of algorithmic flow of the entire system are shown in Figure 5. Four wireless machines are modelled as monitoring control panels under a common name "forwarding junction" as they are used to invoke all the essential interventions required if the health data indicate evidences of stress in the patients.

| Phase Name | Start Phase After | Source | Destination | Source->Dest Traffic | Dest->Source Traffic | REQ/RESP Pattern |
|---|---|---|---|---|---|---|
| SensorToControllerGateway | Application Starts | Originating Source | ControllerGateway | (...) | (...) | REQ->REQ->....RESP->.... (Concurrent) |
| ControllerGatewaytoStorage | SensorToControllerGateway | ControllerGateway | Storage | (...) | (...) | REQ->REQ->....RESP->.... (Concurrent) |
| StorageToReports | ControllerGatewaytoStorage | Storage | Reports | (...) | (...) | REQ->RESP->REQ->RESP.... (Serial) |
| ReportsToControllerGateway | StorageToReports | Reports | ControllerGateway | (...) | (...) | REQ->RESP->REQ->RESP.... (Serial) |
| ControllerGatewaytoMonitoring | ReportsToControllerGateway | ControllerGateway | Monitoring | (...) | (...) | REQ->REQ->....RESP->.... (Concurrent) |
| MonitoringToControllerGateway | ControllerGatewaytoMonitoring | Monitoring | ControllerGateway | (...) | (...) | REQ->RESP->REQ->RESP.... (Serial) |
| ControllerGatewayToSensors | MonitoringToControllerGateway | ControllerGateway | Originating Source | (...) | (...) | REQ->REQ->....RESP->.... (Concurrent) |
| ControllerGatewaytoReports | ControllerGatewayToSensors | ControllerGateway | Reports | (...) | (...) | REQ->REQ->....RESP->.... (Concurrent) |
| ReportsToAnalytics | ControllerGatewaytoReports | Reports | Analytics | (...) | (...) | REQ->REQ->....RESP->.... (Concurrent) |
| AnalyticsToDashboard | ReportsToAnalytics | Analytics | Dashboard | (...) | (...) | REQ->REQ->....RESP->.... (Concurrent) |

Fig. 5 Phases of algorithmic flow of the entire system (Screenshot)

The algorithmic phases shown in Figure 5 are explained as the following:

1) Sensor to controller gateway: sensors sending health data to controller gateway; seven requests per session were configured to represent seven Bluetooth enabled health sensor devices interfacing each mobile app;
2) Controller gateway to storage: controller gateway sending the sensor data to database servers for storage;
3) Storage to reports: a reporting application pulls data from storage for generating the bulk reports to be used for analytics;
4) Reports to controller gateway: the finished reports generated are accessed by the controller gateway;
5) Controller gateway to monitoring: the wireless monitoring stations gain access to the reports through the controller gateway;
6) Controller gateway to sensors: the controller gateway contacts the sensor applications on the mobile phones for data streams required for reports;
7) Controller gateway to reports: the controller gateway contacts the reports server requesting to send its results to analytics server on request of the monitoring stations;
8) Reports to analytics: The reporting server sends its results to the analytics server on request;
9) The analytics server sends its results to the dashboard server, which displays the analytics results for the monitoring stations;

The phases of this algorithm were configured on the devices of the network using their destination settings for simulating each of the phases by their devices. The phases have been planned keeping in mind one of the many configurations possible of the healthcare system to be used for predictive health monitoring, and also considering the feasibility in Kenya. This system does not require Internet as the phases are executed within the edge computing infrastructure run by a hospital monitoring its patients within its last mile coverage. Such hospitals can work in silos as distributed systems but also can be internetworked using Internet for centralised monitoring and governance by the Kenya government. The government may begin by connecting local communities with their serving hospitals through Wi-Fi networking in the first phase and then interconnecting all hospitals in the second phase. The results and discussion are presented in the next section.

## VII. RESULTS AND DISCUSSION

The design presented in Figure 4 and the phases of algorithm presented in Figure 5 were simulated for 18000 seconds (five simulation hours) executing 28,602,748 events in 1 min 6 sec at an average speed of 429,696 events per second. Multiple simulation runs were executed to test validity of the results keeping the network conditions constant. Hundreds of reports were generated covering several network statistics for all the devices. For this research, few most relevant reports are discussed in this section.

The report presented in Figure 6 shows a mapping of the average application packet network delay with the average TCP delay on the network. The average application packet network delay is the average of time taken in packet flows of all the application sessions executing the algorithmic phases logged at every discrete time during the simulation. The average TCP delay is the average time taken by all the TCP sessions in executing their TCP transmissions. If there are no packet losses, the curves for average application packet network delay and average TCP delay should be identical. This is evident in Figure 6, showing their curves in 3D.

 

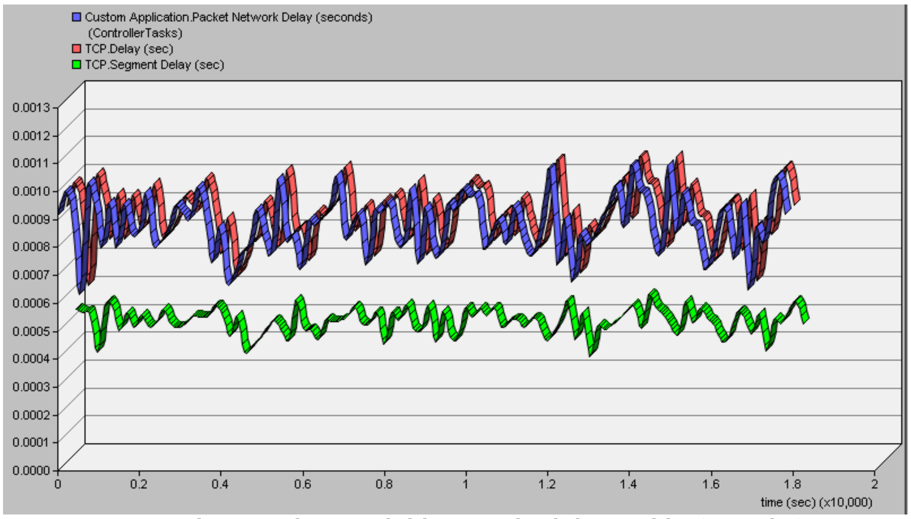


Fig. 6 Application packet network delay mapped with the TCP delay (Screenshot)

The third statistic shown in Figure 6 is average TCP segment delay, which shows the discrete events of average delays experienced by each TCP segment in transmitting their packets. The curve pattern is same albeit showing lower average delays. The average TCP delay and average application packet network delay have varied between 0.7 and 1.1 milliseconds, which is an excellent performance in an edge computing network not connected to the Internet. The traffic on this network is dedicated to healthcare monitoring only. This performance is reflected in the Figure 7, as well, that shows increase in number of connections mapped with application response times (time taken to complete all phases from sensory data collection to the dashboard displays). The numbers of connections are ramping up per mobile phone but the application response times are varying between 1 to 15 seconds. This indicates that there can be a maximum delay of 15 seconds for the health data to be displayed on the dashboard in this configuration. The delay variation caused is because of mobility of the patients, configured at the OPNET default value of 2 km/hr. The mobility of the patients holding the mobile phones and the doctors holding their monitoring stations (like, tablets) need to be considered. Within the simulation time, the sensing to dashboard delay varied between 1 and 15 seconds. This may be considered as near-real-time, and is possible without any Internet connection allowed on the network. The ramping up of connections shown in Figure 7 is due to the unlimited profile runtime configurations. In real world, the connections will stabilize at some stage after initial ramps.

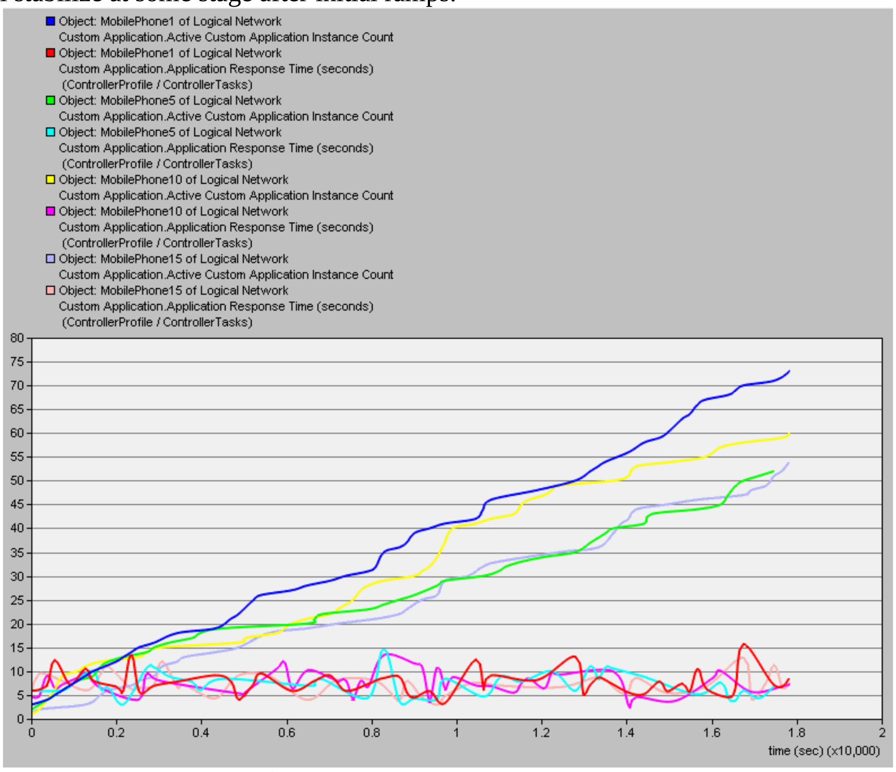


Fig. 7 Increase in number of connections mapped with application response time (Screenshot)

Figure 8 shows the Wireless LAN delays along with some retransmission delays. There were no packet losses when the buffer was set at 256 KB for the 105 health sensors simulated concurrently. The performance did not improve at higher buffer sizes indicating that the retransmissions may be happening because of mobility of the patients. However, this also indicates that buffer size needs to be designed as per the capacity of the sensors planned.

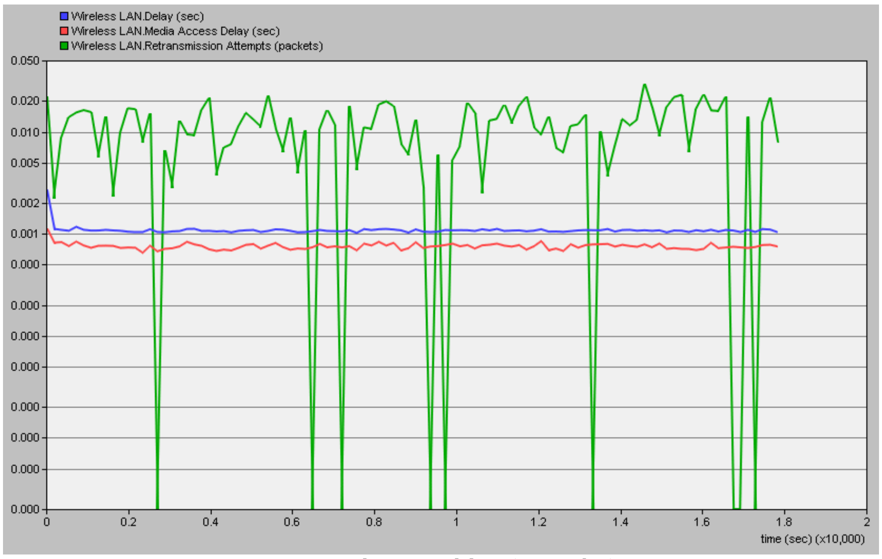


Fig. 8 Wireless LAN delays (Screenshot)

Figure 9 shows the TCP congestion windows experienced by the sampled TCP sessions of five mobile phones. Longer the windows, lower are the congestions; but the window is formed with fixed bytes sizes depending upon the TCP delays. Figure 9 shows long TCP congestion windows stretching over the entire simulation period for each session sampled indicating zero congestion.

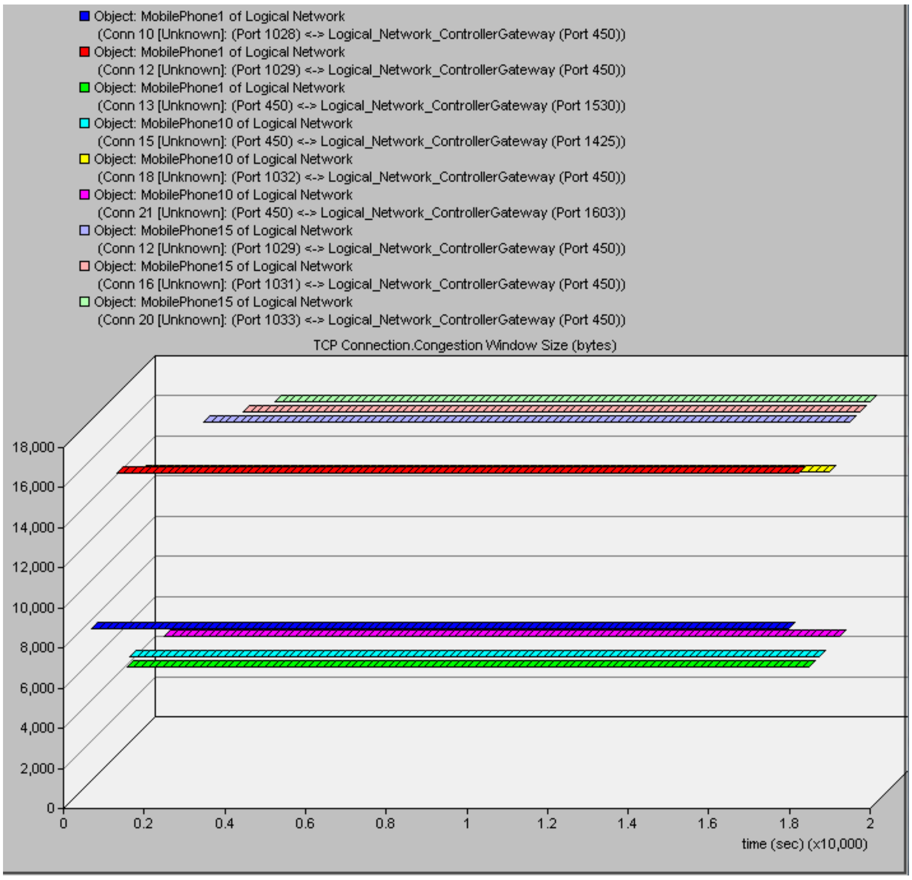


Fig. 9 TCP segment delays (Screenshot)

However, the byte sizes varied by sampled sessions for each of the mobile phones indicating effects of TCP delays. This reflects that such effects cannot be avoided even in a network designed specifically for predictive healthcare. Thus the predictive healthcare networking needs to be designed with near real time performance. Further, it also indicates that mixing healthcare data with Internet data will be ineffective given the huge amounts of video viewing and streaming occurring on the Internet as a regular practice. For example, one can imagine the predictive healthcare services collapsing when a sports event is happening in a locality. These are some of the crucial and relevant observations made in the simulations. A general conclusion is presented in the next section based on these are other observations made.

## VIII. CONCLUSIONS

The The simulation results suggest that the regular network used for Internet access should not be used for predictive health monitoring. A private network comprising of several customizations are needed in the information and networking components to make them fit for predictive health monitoring. The servers deployed in the fog/edge computing should be of high capacities and the Wi-Fi routers should have high capacity of buffer memories used for storing health data streams temporarily. The Wi-Fi routers should have a large number of receiving channels to avoid information losses. The TCP session timeouts, packet losses, and short TCP windows indicating network congestions can be very harmful for individuals being monitored critically. They should be avoided by the designer even if the cost of networking is higher. The sensors may be attached as individual devices or as body area networks. The bandwidth allocation to individual sensors or entire body area networks should be planned based on the frequency and amount of data needed by the hospitals. The sensors or entire body area networks deployed on individuals should have carefully conducted right sizing of number of parameters, their data volumes, transmission frequencies, and criticality of the individuals. The hospitals should classify patients in different classes based on criticality, data volumes, and frequencies of monitoring needed, and allocate appropriate multi-tiered body area networks for the different patient classes. A one size fit for all approach will fail. Finally, the effect of mobility is clearly reflecting in the simulation results. The application response times (delay from sensor data transmission to dashboard display) varied from 1 to 15 seconds because of mobility. Hence, it is recommended that the individuals under critical monitoring should not be allowed high mobility as it has a negative effect on monitoring reliability and effectiveness.

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