JEAS

JOURNAL OF ENGINEERING AND APPLIED SCIENCES

Journal of Engineering and Applied Sciences, Volume 20, Number 1, June 2022, 657 - 668

Internet of Things (IOT) Clustered Recursive Routing Chain Architecture for Low Latency Diffusion: New prospects for Nigeria Health care system

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Abstract
In this paper, a novel Recursive Edge-Cloud Orchestration Infrastructure is investigated. The System characterization for recursive Routing Network (RRN) architecture using computational modeling is achieved. Bayesian Machine learning technique is introduced for the IoT access control into the cloud. Established complexity-driven algorithms are derived for network orchestration. The system leverages robust design architecture, and availability data center model for end-to-end services and communication for service provisioning. To ensure service accessibility for each IoT device in a cluster, an unbiased uniform estimator was computed for the data-center model. A computational service-oriented software modularization framework is derived for IoT edge sensors. Simulation of the Cloud-Fog orchestration infrastructure is done using Riverbed Modeler V.17.5 to determine the responsiveness of QoS metrics in a validation study. Simulation results reveal that the proposed offloading optimization strategy built into Recursive routing network (RRN) architecture is resilient. With Restful-Application Programmable Interface(R-API) and Recursive routing chain algorithm (RRCA), the proposed algorithm outperforms the other selected model in terms of cost economy, throughput, latency, and utilization metrics. The work suggests that IoT edge sensing and monitoring solutions infused on the device hardware can greatly improve service delivery and reduce maternal mortality significantly in Nigeria.

Keywords: Cloud computing, Quality of Service Internet of things, low latency diffusion, Recursive routing chain architecture, Fog Computing

1. Introduction

The Nigerian health care system has suffered several down-falls despite its strategic position in Africa and other developing nations; as the country is greatly under-served in the health care sphere. For decades, communicable diseases outbreak has been a threat not only to the lives of individuals but also to national security. The health care system in Nigeria and some other developing countries require strong leverage on disruptive technologies such as the Internet of things (IoT) and cloud computing (Okafor, *et al*, 2017). These technologies can fix the issues of obsolete facilities and infrastructures which have continued to increase mortality rates especially among children and pregnant women in both rural and urban areas (Senate, Federal Republic of Nigeria, 2008; Okaro, Ohagwu, and Njoku, 2010).

IoT/Everything network cluster innovations has been applied in Cyber-Physical systems (Okafor, *et al*, 2021). This offers a system of interrelated communication/computing, mechanical/smart devices, objects, animals, or people unique identification for data transfer over a complex network without human-to-human (H2H) or human-to-computer interaction (H2CI)(Zhong, Vincent, Mario, and Wei**,** 2019**)**. With IoT clusters, the executions of a variety of complex tasks in health care systems become more feasible and easier as the quality of service (QoS) demands are expressed in terms of high-level communication requests. These are characterized by the different requirements of sensing/actuating functions, processing, memory needs, low latency, throughput, etc (Wu, Wu &Yuce, 2019). Despite the enormous benefits offered by IoT/Everything, most critical systems such as health care delivery have not embraced IoT for efficient services. In cases of data-in-motion, non-invasive precision IoT clusters require reliable connection availability. This in turn requires modeling the survivability demands of IoT virtual networks (VNs) for robust device and inter-device resource sharing (Cisco, 2017). Few indigenous IoT-Cloud service providers for Non-invasive signal propagation are investigated and compared with the non-invasive Spine-leaf IoT network model (Okafor *et al*, 2017). Software integrated licensed libraries such as Python dynamic link library and Riverbed application program interface considered. Recursive routing networks that comprise set of service-oriented functions typically organized into a grid and a meta-learner decision-making component called the IoT Fog router gateways are introduced. These are proposed for data scalability, low latency, and high throughput models.

The aim of this paper therefore is to develop an IoT clustered recursive routing chain algorithm (RRCA) for low latency diffusion in Nigerian health care systems. This will proffer numerous solutions to poor monitoring and service delivery that has lead to unnecessary delays at large as seen in Nigeria Health care systems. The scope is delimited to the analytical design prototype and simulation of health architecture with its operational steps and a use-case scenario which will be presented for validation. However, researchers have extensively applied the Internet of Things (IoT) and cloud computing systems in various sectors such as health, transport, environmental, power systems, etc. But the idea of Clustered Recursive Routing Chain Architecture for Low Latency Diffusion will change computational contexts in various health Care Systems. A review of various efforts on IoT Cloud applications and their methodologies are presented. Kotani (2019) considered IoT services making demands on network resources and presented network architecture with a network controller that automatically estimates and prioritizes important traffic in mission-critical scenarios. The proposed controller in the architecture provided three interfaces for interaction with IoT devices, service providers, and users. The drawback was absence of clustering and zero supports for Survivable Virtual Network Embedding.

In the work by Riaz et al (2015), a non-homogenous grid system was designed to gather patients' vital signs, temperature, oxygen, pressure, etc. The system employed cloud storage in capturing patients' data set from a sensor via data-aggregation for patients monitoring on-demand. But the absence of optimal handling of IoT node joins or exits in Clusters that affected QoS managements was a major shortfall. Also, High Maintenance costs as there was the absence of established standards/specifications in these systems were a burden on the end-users. The architectural representation of an e-health monitoring system was also modelled in Guto Leoni *et al* (2018). Its behavioral model depended on sensing devices, Raspberry Pi2 Fog node, and Cloud services for the processing and storing of its vital signal datasets. The system involved sensor detection such as blood-sugar capture, heart beat monitoring, and epilepsy sensing. However, the issue of device-to-device interoperability and harmonization was a big challenge as coordination appears to pose a major problem. Thus, a huge aspect of the systems integration is based on local materials/interfaces that do not align with established standards.

Wu, Wu, and Mehmet Rasit (2019) also developed a wearable body area network IoT linked system for safety and health cases especially in industrial environments. The environmental and physiological metrics were captured using the wearable. A heterogeneous platform driven by Bluetooth communicated vital medical signs via distinct gateways into its Cloud connections. Harmful and non-harmful environments were monitored with instant notification or early warning for end-users. But in these systems, no clarity incentives and payback structure were specified to the providers as reimbursement periods for these digital healthcare systems are not aligned with healthcare technology budget allocations/investments. Another interesting perspective to this review is the Bayesian linear programming without IoT infusion found in the literature below.

Hadi *et al*, (2020) explored Bayesian linear programming to achieve a cognitive and self-optimizing network that proactively adapts not only to channel conditions but also according to its users' needs. The work used three machine learning (ML) algorithms, namely, naïve Bayesian (NB) classifier, logistic regression (LR), and decision tree (DT), as an ensemble system to analyze historical medical records of stroke out-patients (OPs) and readings from body-attached internet-of-things (IoT) sensors to predict the likelihood of an imminent stroke. Maksimov, *et al*, (2020), applied the theory of algebraic Bayesian networks for deriving knowledge consistency patterns using computational complexity programming methods. Yang, *et al* (2021), proposed an approach of epitasis detection using integer linear programming optimizing Bayesian Network. The work compares integer linear programming Bayesian network (ILPBN) with epistasis mining algorithms using simulated and real Age-related macular disease (AMD) dataset.

Chen & Frazier (2016) presented a Bayesian sequential decision-making formulation involving an information filtering problem. The Bayesian linear model was used to compute a computational upper bound on the value of the optimal policy. Other Bayesian linear models applied in computational real-time processes have been studied by Miyamoto et al (2020), Zhu et al. (2017), Tamura, (2018), Zhou et al (2021), and Wei Pan (2017). To the best of the authors' knowledge, existing literature has failed to apply Bayesian linear models within "IoT recursive routing algorithms and architectures for low latency diffusion. Hence, the current work presents a robust and recursive routing algorithm for low latency diffusion that tackles the challenges of QoS concerns considering micro-services in the Cloud. The idea is to improve health care architecture at the lowest cost. The optimization problem of resource allocation is formulated in the Bayesian naive's linear programming (BNLP) model. This is used for optimal access control by the embedded IoT clusters. It is applied to achieve more flexible and efficient resource allocation for uncertain and heterogeneous traffic. The work also covers a high degree of heterogeneity among the IoT clusters and integration of virtual IoT devices, gateways, and micro-granular architectures. The proposed balanced routing scheme for integrating micro-services will offer flexibility and scalability in the architectural models for low latency diffusion in IoT Clusters. A prototype of the enhanced health architecture with its operational steps and a use-case scenario will be presented for validation.

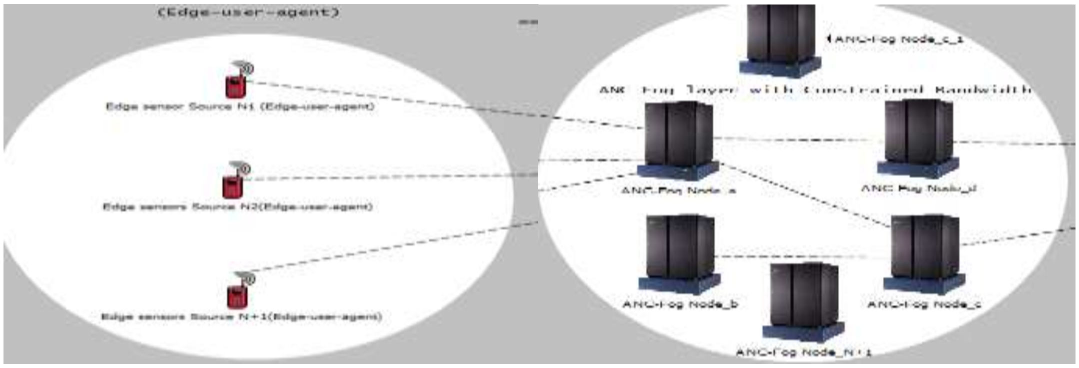
2.0 Material and methods

This section presents a novel computational research approach for IoT-driven Bayesian naive's linear programming (IoT-BNLP) characterization. The core materials and tools employed in the research include C++ Modeller Library & Engines, Minitab 12.0, MATLAB 17.0, PIC Controllers, and IoT Edge sensors. A developed recursive Routing Network algorithm (RRCA) is incorporated into the established recursive architecture in several ways; first by adding them to device representation layers, recurrent network hidden layers, and classifier layers. The evaluation task is discrete event natural language inference (DENLI). The IoT-BNLP methodology is implemented on a hybrid multi-cloud using Service-oriented Architecture (SOA). The computational modeling technique was used to derive the RRCA and was incorporated into a novel interconnect topology (i.e., DCell recursive architecture).The evaluation task was carried out with Discrete Event Natural Language Inference (DENLI) using the C++ Library-based modeler 17.5. The model components are fine-tuned to the inferential signatures that are characteristic of high availability, low latency, and QoS metrics. Using the C++ Library-based modeler 17.5, the RRN's routing decisions which reflect the high-level genre structure of QoS metrics was evaluated

2.1 Test bed Experiment

In this Section, the use case scenarios explored to test and validate the established algorithms and the selected Datacenter Networks (DCN) are described. The instance-based scenario is used to compute workload drain for the DCN. A fundamental assumption is that the Discrete Environment Simulation (DES) comprises a Cloud DCN having 3 IoT edge users, 6 IoT edge Fog layers, and 3 IoT synchronized expert virtualized servers.

Each of the virtualized host-machine has multiple CPU cores; 8 GB of RAM, and 8TB SAN (8 terabyte Storage Area Network) storage. In the DES in Figure 1, multiple Virtual Machines VMs, are running on the individual machines having these constraints: $1+n$ CPU core, with 1000 MIPS(million instruction per second) computing capacity, 1GB RAM, and 16 GB SAN. A baseline policy assigns each VM to the deployed hosts where each host-machine dynamically assigns the VM capacity concurrently. The VM scheduler is time shared via the profile configuration. In all cases, a non-invasive Spine-leaf IoT network model was contextualized for BNLP.



(a) Edge node layered model **(b) Fog layered model.**

Figure 1. Recursive Edge- Fog Model

Another interesting element is the *Vm*Load Balancer. This is used to identify *Vms* for cloudlet assignment in the data center processing. This load balancer is a hybrid (round-robin, uniform execution load, and throttled load balancer). After the simulation, the output panel displays the response time for each user base. The Riverbed simulator offered a complete result screen indicating the response time for each user, service request time by each network element, and many other service requests by the data center. Three complexity algorithms are introduced for evaluations of the complex health care architecture. Also, three use case scenarios were investigated and considered during the simulation study in Figure 1 viz: Cloud Fog orchestration DCell R-API (Novel Interconnect Topology, (i.e., DCell-Restful Application Program Interface) Wang,(2015), LaSDaA (Layered Scalable Data Centre) optimization algorithm(i.e. LaSDaA R-API- Layered Scalable Data Centre-Restful Application Program Interface) Chkirbene, *et al*, (2020), and IoT-Clustered Recursive Routing Chain algorithm (RRCA R-API- Recursive Routing Chain algorithm-Restful Application Program Interface).The IoT edge services simulation result browser environment and the compilation simulation corridor are depicted in Figure 1. Figure 2 shows the successful IoT Edge-to-Cloud services compilation.

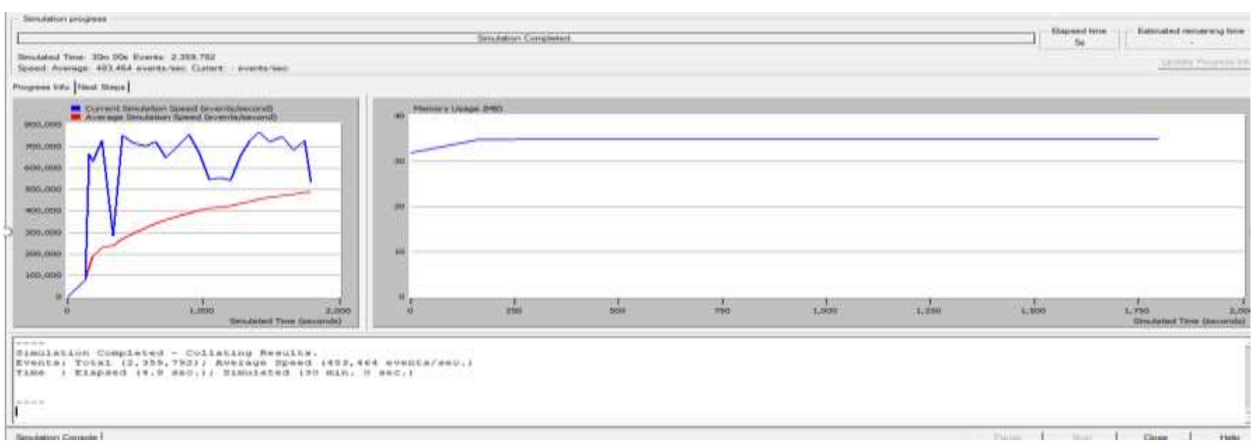


Figure 2: Successful IoT Edge-to-Cloud Services Compilation Simulation

2.1.1Optimization Model Formulation

In this section, we present the IoT-BNLP using a probability model for the e-Health access control and determine an unbiased estimator for uniform assessment of the platform irrespective of the location of patients. From Okafor et al, (2021), the BNLP model is formulated as follows:

Let $A_i = x_i$; $i = 1, 2, \ldots, n$

Where $\boldsymbol{A_i} = \boldsymbol{x_i}$ is random variables for the IoT-BNLP patients in the proposed system.

$$P(A_i = a_i) = P(X_i = x_i)$$

The probability that the random variable A_i assumes a value a_i is equal to the probability that the random variable X_i assumes value x_i. But $P(x_1) = P(x_2) = \ldots = P(x_n)$

The probability mass function is well adapted for IoT-BNLP

$$P(X_1 = x_1) = \frac{\theta^x \exp(-\theta)}{x!}; \quad x = 0,1,2,\cdots,\infty \quad \text{(PMF of Poisson distribution)}$$

Since the random variables follow the Poisson distribution, the probability mass function (pmf) is given above. The above PMF is written as in Equ. (1) for one of the random variables.

$$P(x_1;\theta) = \sum_{x=0}^{\infty} \frac{\theta^x \exp(-\theta)}{x!} \tag{1}$$

For many of the random variables (many patients), let Equ (1) be rewritten in Equ (2).

$$P(x_1;\theta_1) = P(x_2;\theta_2) = \cdots = P(x_n;\theta_n) \tag{2}$$

But since each of the random variables transacts business with the server at a given time, that is, $P(x_i's)$ is associated with time, then, $\theta = \theta t$,

$$\therefore P(x_1;\theta t) = \sum_{x=0}^{\infty} \frac{(\theta t)^x \exp(-\theta t)}{x!} \tag{3}$$

Equ. (3) is a non-homogenous Poisson process with parameters θt .

The likelihood (joint distribution) function of the distribution in Equ.(3) is given as

$$P(x_n;\theta t) = \prod_{x=1}^{n} \frac{(\theta t)^x \exp(-\theta t)}{x!} \tag{4}$$

Equ. (4) can be written as Equ. (5).

$$P(x_n;\theta t) = \frac{(\theta t)^{\sum x_i} \exp(-\theta t)}{\prod x!} \tag{5a}$$

For the IoT-BNLP characterization, the random IoT variables must have equal mean access to the Cloud server service facility. Therefore, it is necessary to remove the effect of time by describing the intensity of the Poisson process with the Power Law Process (PLP). Power Law process is a class of non-homogenous Poisson. The mean function of the PLP is given by Equ (5b)

$$\Lambda(t) = \theta t^b \tag{5b}$$

The intensity function of PLP is given as

$$\frac{d}{dt}\Lambda(t) = \theta b t^{b-1} \tag{5c}$$

Let $\theta = a$, then

$$\frac{d}{dt}\Lambda(t) = a b t^{b-1} \tag{5d}$$

Where ***b***= the shape parameter, ***a*** = the intercept on $\Lambda(t)$ axis. If ***b*** = 1, we have HPP(θ) ; implying that we have stationery increment; if ***b***>1, or b < 1, we have NHPP(θt) with either increasing or decreasing intensity. We determine ***a*** and ***b*** from Equ. (6).

$$\log_e \Lambda(t) = \log_e a + b\log_e t \tag{6}$$

Where ***b*** = slope; ***a*** = intercept on $\log_e \Lambda(t)$.

A plot of $\log_e \Lambda(t)$ against $\log_e a$ will give the value of b, the slope.

Hence, we write re-write Equ (5a) as Equ (7a).

$$P(x_n;\theta) = \frac{(abt^{b-1})^{\sum X_i} \exp(-abt^{b-1})}{N!} = \exp(-abt^{b-1})\{\frac{(abt^{b-1})^{\sum_{i=1}^{n} x_i}}{S}\} \tag{7a}$$

Equ (7a) can now be written as Equ. (7b) which is the probability model for the IoT device edge transaction using IoT-BNLP paradigm

$$P_n(t) = \exp\{-abt^{b-1}\}\left[\{abt^{b-1}\}^n\right]/n! \tag{7b}$$

Equ. (7a) gives the derived IoT-BNLP probability of the number of transactions per patient at a given time ***t***. The probability model is used to determine the prior probability of active patients. To determine the posterior probability for the system, the derived composite Bayesian linear model in Equ. (8) is enforced among all the participating edge to cloud patients at ***t***.

$$P(y_{Ai}/\theta_{A_i}) = \frac{P(\theta_{A_i}).P(y_{A_i}/\theta_{A_i})}{\sum_{i=1}^{n} P(\theta_{A_i}).P(y_{A_i}/\theta_{A_i})} = \frac{P(abt^{b-1}{}_{A_i}).P(y_{A_i}/abt^{b-1}{}_{A_i})}{\sum_{i=1}^{n} P(abt^{b-1}{}_{A_i}).P(y_{A_i}/abt^{b-1}{}_{A_i})} \tag{8}$$

where $P(y_{Ai}/\theta_{A_i})$ is the probability of obtaining information about patient $\boldsymbol{A_i}$ given that we previously had the health history about $\boldsymbol{A_i}$ at time ***t***. A key meta-data information for any patient using the IoT-BNLP approach is the PIN identifier *P*.

Let the random number (PIN code) associated with each patient be represented such that $x_i = r_{A_i}, r_{A_i} \subset A_i$ or $r_{A_i} = A_i$ stored in the Cloud server alongside with the patient information on the overall ***A_i's*** in the memory. The probability that the information stored about ***A_i's*** in ***(M)*** correspond to the one in the server memory ***(N)*** is given by Equ. (9)

$$P(r_{A_i}) = P(r_{A_i}/y_{A_i}) \tag{9}$$

But

$$\therefore P(r_{Ai}/y_{A_i}) = \frac{P(r_{A_i}).P(y_{A_i}/r_{A_i})}{\sum_{i=1}^{n} P(r_{A_i}).P(y_{A_i}/r_{A_i})} = P(y_{Ai}/\theta_{A_i}) \tag{10}$$

And since the information (PIN) stored about ***A_i's*** in **(M)** corresponds to the one in the server memory (N), Equ. (10) remains valid. Therefore, Equ. (10) is seen by the system as Equ. (8). But since Equ (8) is the one whose parameters are known, this can then be computed in place of Equ. (10), since the system matches the PIN with the meta-data information about the patient.

Finally, the constructed uniform minimum variance unbiased estimator **($T_{n(x)}$)** that will give equal access time to all IoT tagged patients (i.e mean rate of accessing the server at all times by the ***A_i's*** using their respective ***r_{Ai}***) irrespective of the locations of ***A_i's***, and it is given in Equ. (11).

$$T_{n(x)} = \frac{y(y-1)}{n^2} \tag{11}$$

where y is the IoT-tagged device sufficient statistic given by

$$y = (n + a)^n = \sum_{i=1}^{n} \binom{n}{k} x^k a^{n-k} \quad (12)$$

Where n = scalability factor, $\boldsymbol{k}$ =correction factor. From Equ 12, the Bayesian naive's linear programming (BNLP) construct applied for IoT tagged patients allow access authentication into the cloud experts system server considering Equ. (7b) and (10) respectively. To introduce the characterized RRN model for UMVUE that handles service availability in the network, the derivation of the computational model is further implemented with the Bayesian machine learning technique during the simulation validation. Also, an unbiased uniform estimator for service accessibility in RRN processes has been determined. The Algorithm I shows the harmonized service availability with API cryptographic for secured RRN processes. Data presentation/analysis is derived accordingly. Algorithm II shows the logical traffic workload flow processes for RRCA.

Algorithm I. RRCA Predictor for Low Latency QoS Allocation

```
1:  Inputs:        IoT-tagged nodes_Control-CallSchedule
                   History of IoT compute resources, QoS Provisioning and transactional workflow
    Output:        RRCA_DES
    Parameters:        RRC_weight←Empty; // IoT weighted Moving Average
                       RRC_weight ContainerhistoryItem← null; // QoS Pattern
    int i←0;
    While I<T_n(x)_monitorCallSchedule d do
        historyItem←HistoryList.get ( HistoryList.Size() – IoT_monitorCallSchedule – i )
        IoT_weight←ClusterA + ClusterB
        IoTweightedMoving←IoTweightedMoving+ (ContainerhistoryItem * weight);
        total IoT_weight←total IoT_weight + IoTweight;
        i ++;
    end while
    IoT_DES←IOTweightedMoving / totalIOTWeight;
    // Calculate Dynamic low latency
    initialValue←(y * IoT_weight) + (1 –y) * (pastInitialValue + trendPosteriorValue);
    trendPosteriorValue←y * (initialValue - pastInitialValue)+ ((1 – y) * pastTrendPosteriorValue);
    IoT_DES←initialValue+ trendPosteriorValue;
    ReturnIoT_DES
```

Algorithm II. Fault Free RRCA

```
1:  Inputs:        IoT_Edge nodes as vector directly connected clusters
                   ( S2,S1 ) is the source coordinates
                   ( D2,D1 ) is the destination coordinates
    Output:        The path is the path from the source to the destination
    Procedure:       Fault Free Routing ((S2,S1 ), (D2,D1 ), Ω)
    int i←0;
    While I>∞
        if S2 = D2then
        /∗The source and the destination are in the same
              cluster and are directly connected via an external
               switch /∗
        Path ←(S2,S1 ) →(D2,D1 )←(S2,S1 )
```

else
if (S_2 −D_2) mod $n^3/2$ ∈Ω ***then***
/∗The source and the destination are directly connected /∗
Find T12 and T11 such that P ← (S2, S1) →(S2,T 11) →(D2,T 12) → (D2,D1).
else if (S2 −D2) mod $n^3/2$ ∈ Ω ***then***
/∗The source and the destination are not directly connected and are linked only by the intermediate of switch e s/∗
Find T 11 , T 12 , T 21 and T 22 such that P ← (S_2 ,S_1) → (T i2 ,T i1) → (T j2 ,T j1) → (D2 ,D1)
where (*i, j*) is an arrangement of {1,2}
else
/∗The source and the destination are not directly connected and are linked only by the intermediate of 3 switches e s/∗
Find T 11 , T 12 , T 21 , T 22 , T 31 and T 32 such that P ← (S2 ,S1) → (T i2 ,T i1) → (T j2 ,T j1) → (T k2 ,T k1) → (D2 ,D1) where (i, j, k)is an arrangement of {1,2,3}.
end if
end if
Path ←P
end procedure

To implement the RRN based on the IoT-BNLP model, a simulation of the patients transacting a given number of function calls ***(n)*** with the server (expert doctor) at any given time ***(t)*** was carried out using MINITAB 16. This was used to simulate the number of transactions each customer made (average) at a given time ***t***.

3.0 Results and Discussions

3.1. IoT Edge-to-Cloud Data Stream Throughput

With the injection of the IoT BNLP scheme, the throughput captured here refers to the stream's data rate (bits per second) generated by the IoT edge application service at the edge sensor. Figure 3 shows the Plot of edge node data stream Throughput against Edge Workload. Compared with the IoT Edge Cloud Fog orchestration infrastructure, in the proposed scheme, when the number of IoT edge devices is between 200 and 2000, it was observed that the linearized throughput tends to be stable as the average number of edge devices used per unit of time increases gradually. The trend indicates that the system throughput capacity and resource utilization are not saturated especially with the RRCA-TCP (Transmission Control Protocol) algorithm. Therefore, the system can sustain throughput access success probability near 100% and the average volume of IoT data stream transmitted per patient increases steadily. As a result, the throughput increases linearly. With the further increase in the number of devices greater than 2000, the throughput probability begins to experience an overshoot while being stable. When the number of devices achieves 40 bytes/sec throughput, the access success probability is still close to 33.22% for the RRCA-TCP algorithm. In the case of the DCell TCP algorithm, the performance of the base station is up to 32.39% and 34.29% for LaSDaA. Thus, the IoT data stream becomes more stable as the RRCA throughput rises with its closed-loop controls.

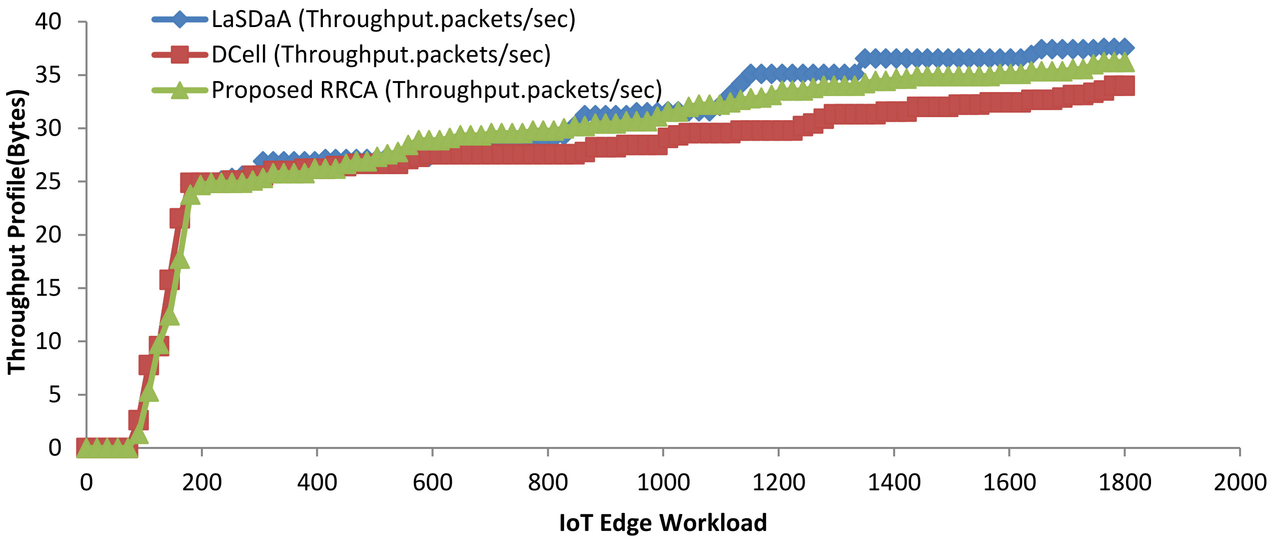


Figure 3: IoT Data stream Throughput service

This shows that both algorithms can carry substantial data streams and stabilize at the maximum workload. With the increase in the number of IoT edge devices, the performance degradation resulting from random access and data transmission (which normally leads to deterioration of system performance) is completely impossible.

3.2. IoT Edge-to-Cloud Data Stream Bandwidth Utilization

From the Edge Fog application perspective, data stream bandwidth utilization deals with the network capacity to transmit data from the edge to the cloud. Compared with both the IoT Cloud Fog orchestration infrastructure-DCell TCP algorithm and LaSDaA optimization algorithm, bandwidth is optimally utilized in the proposed RRCA-TCP. Figure 4 shows the Plot of IoT Data stream bandwidth availability for the traffic workload. In the proposed scheme, when the number of IoT edge devices is between 200 and 2000, it was observed that the oscillatory trends tend to be stable as the average number of edge devices used per unit of time increases gradually. The trend indicates that the system bandwidth utilization capacity is considerably high especially with the RRCA-TCP R-API algorithm. Therefore, the system can do more processing using RRCA-TCP compared with other algorithms. The maximum bandwidth utilization profiles for RRCA-TCP (R-API), DCell-TCP (R-API), and LaSDaA-TCP (R-API) are 82.2%, 16.57%, and 1.23% respectively. This shows that the proposed RRCA algorithm can carry substantial data streams and be stabilized at the maximum workload.

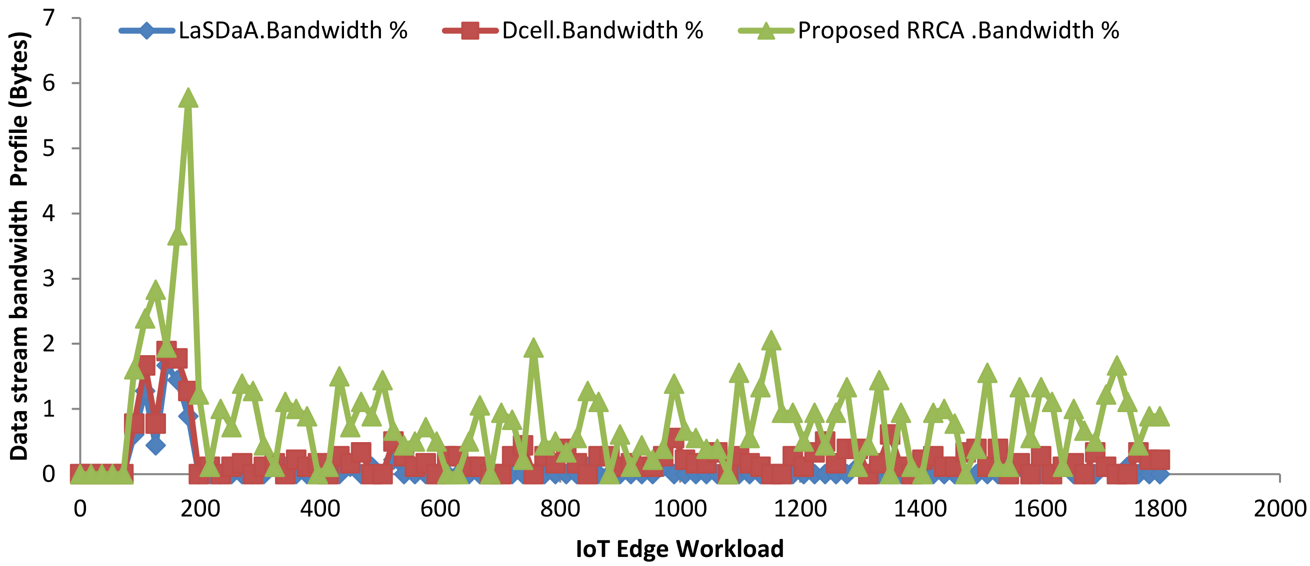


Figure 4: IoT data stream bandwidth Vs Edge Workload

3.3. IoT Edge-to-Cloud Data stream Latency

Figure 5 shows the plot of the IoT edge data stream latency profile against the traffic workload. Latency explains how fast the network is in packet/data stream delivery. From the Edge Fog application perspective, data stream latency deals with the bi-directional edge to Cloud traffic flows. Compared with both the IoT edge to Cloud Fog orchestration infrastructure optimization algorithm, a relatively low latency behavior was observed in the proposed RRCA-TCP. From the proposed scheme, when the number of ANC edge devices is between 200 and 2000, it was observed that the latency profiles for RRCA-TCP (R-API), DCell-TCP (R-API), and LaSDaA-TCP (R-API) gave 10%, 30%, and 60% respectively. This shows that the proposed algorithm can carry substantial data streams and stabilize at the maximum workload.

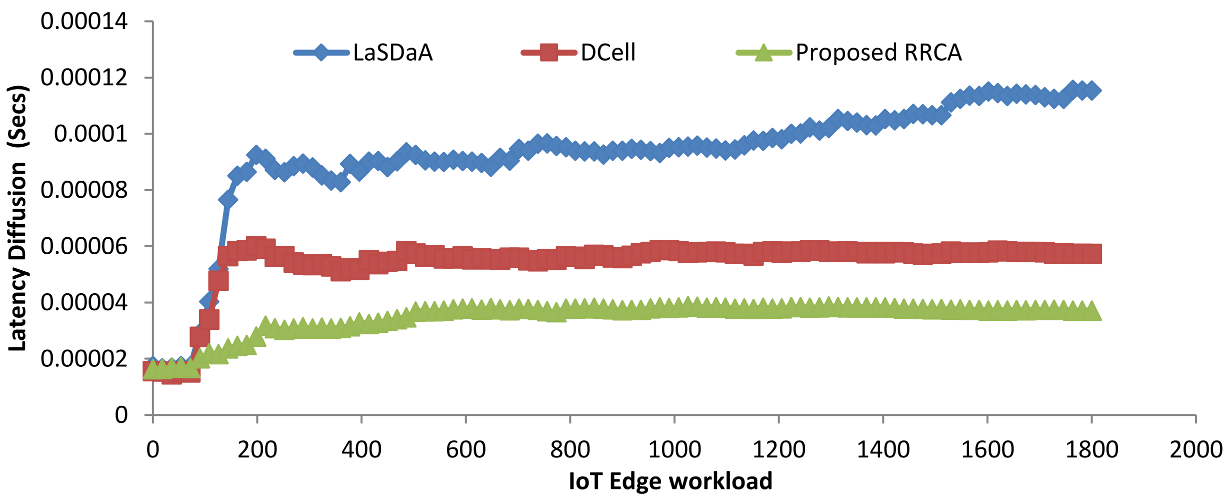


Figure 5: IoT Edge-to-Cloud latency Profile

4.0 Conclusions

This paper has presented an Internet of Things-based Clustered Recursive Routing Chain Algorithm for low latency diffusion. This is proposed for the revitalization of the ailing and weak Health Care System in Nigeria and other Developing countries. The work showed the IoT-BNLP constructs and their computational characterizations. From the validation study, the IoT-Fog backbone distributes workloads across multiple computing resources, such as server clusters, network links, central processing units, or disk drives. The system is shown to offer optimized resource utilization, maximize throughput, and maintain low latency response even on heavy traffic workloads. The work shows that with multiple components and layered load balancing, reliability is feasible through cascaded redundancies. This has made room for a robust health care support system in context.

5.0 Recommendations

A new policy and legislation are recommended to drive the system. Multiple critical stakeholders can further be engaged for improved health system architecture before deployment. Data protection and privacy should be seriously managed to reduce litigations. Future studies will focus on deep learning network optimization, mobile application integration, and predictive analytics.

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